بِسْمِ اللهِ الرَّحْمنِ الرَّحِيمِ

Depression Anxiety Stress Scales Responses

(1) Identify Columns

Part One (Q) :

Column	Identifications
Q1	I found myself getting upset by quite trivial things.
Q2	I was aware of dryness of my mouth.
Q3	I couldn't seem to experience any positive feeling at all.
Q4	I experienced breathing difficulty (eg, excessively rapid breathing, breathlessness in the absence of physical exertion).
Q5	I just couldn't seem to get going.
Q6	I tended to over-react to situations.
Q7	I had a feeling of shakiness (eg, legs going to give way).
Q8	I found it difficult to relax.
Q9	I found myself in situations that made me so anxious I was most relieved when they ended.
Q10	I felt that I had nothing to look forward to.

Column	Identifications
Q11	I found myself getting upset rather easily.
Q12	I felt that I was using a lot of nervous energy.
Q13	I felt sad and depressed.
Q14	I found myself getting impatient when I was delayed in any way (eg, elevators, traffic lights, being kept waiting).
Q15	I had a feeling of faintness.
Q16	I felt that I had lost interest in just about everything.
Q17	I felt I wasn't worth much as a person.
Q18	I felt that I was rather touchy.
Q19	I perspired noticeably (eg, hands sweaty) in the absence of high temperatures or physical exertion.
Q20	I felt scared without any good reason.
Q21	I felt that life wasn't worthwhile.
Q22	I found it hard to wind down.
Q23	I had difficulty in swallowing.
Q24	I couldn't seem to get any enjoyment out of the things I did.
Q25	I was aware of the action of my heart in the absence of physical exertion (eg, sense of heart rate increase, heart missing a beat).
Q26	I felt down-hearted and blue.
Q27	I found that I was very irritable.
Q28	I felt I was close to panic.
Q29	I found it hard to calm down after something upset me.
Q30	I feared that I would be "thrown" by some trivial but unfamiliar task.
Q31	I was unable to become enthusiastic about anything.
Q32	I found it difficult to tolerate interruptions to what I was doing.
Q33	I was in a state of nervous tension.
Q34	I felt I was pretty worthless.

Column	Identifications
Q35	I was intolerant of anything that kept me from getting on with what I was doing.
Q36	I felt terrified.
Q37	I could see nothing in the future to be hopeful about.
Q38	I felt that life was meaningless.
Q39	I found myself getting agitated.
Q40	I was worried about situations in which I might panic and make a fool of myself.
Q41	I experienced trembling (eg, in the hands).
Q42	I found it difficult to work up the initiative to do things.

Identify Some Symbols

Symbols	Identifications
A	This response is stored in variable (e.g. Q1A).
E	The time taken in milliseconds to answer that question (e.g. Q1E).
I	Question's position in the survey (e.g. Q1I).

Identify Some Answers

Scale	Description
1	Did not apply to me at all.
2	Applied to me to some degree, or some of the time.
3	Applied to me to a considerable degree, or a good part of the time.
4	Applied to me very much, or most of the time.

See This Photo for How This Looked 😳 !!!

In the past week...

I felt that I had nothing to look forward to.

- ○ Did not apply to me at all
- ○ Applied to me to some degree, or some of the time
- ○ Applied to me to a considerable degree, or a good part of the time
- ○ Applied to me very much, or most of the time

↻ redo last question 5 / 42

Part Two(other durations were also recorded & measured on the server's side) :

Column	Identifications
introelapse	The time spent on the introduction/landing page (in seconds).
testelapse	The time spent on all the DASS questions (should be equivalent to the time elapsed on all the individual questions combined).
surveyelapse	The time spent answering the rest of the demographic and survey questions.

Part Three (TIPI) :

The Ten Item Personality Inventory was administered (see Gosling, S. D., Rentfrow, P. J., & Swann, W. B., Jr. (2003). A Very Brief Measure of the Big Five Personality Domains. Journal of Research in Personality, 37, 504-528.) ":

Column	Identifications
TIPI1	Extraverted, enthusiastic.
TIPI2	Critical, quarrelsome.
TIPI3	Dependable, self-disciplined.
TIPI4	Anxious, easily upset.
TIPI5	Open to new experiences, complex.
TIPI6	Reserved, quiet.
TIPI7	Sympathetic, warm.
TIPI8	Disorganized, careless.
TIPI9	Calm, emotionally stable.
TIPI10	Conventional, uncreative.

The TIPI items were rated "I see myself as:" _____ such that

Scale	Description
1	Disagree strongly
2	Disagree moderately
3	Disagree a little
4	Neither agree nor disagree
5	Agree a little
6	Agree moderately
7	Agree strongly

Part Four (VCL) :

Column	Identifications

VCL1	boat
VCL2	incoherent
VCL3	pallid
VCL4	robot
VCL5	audible
VCL6	cuivocal
VCL7	paucity
VCL8	epistemology
VCL9	florted
VCL10	decide
VCL11	pastiche
VCL12	verdid
VCL13	abysmal
VCL14	lucid
VCL15	betray
VCL16	funny

Identify Some Answers

Scale	Description
0	Unchecked
1	Checked

Part Five (General Info) :

A bunch more questions were then asked":

Column	Identifications
education	How much education have you completed?

Identify Some Answers

Scale	Description
1	Less than high school
2	High school
3	University degree
4	Graduate degree

Column	Identifications
urban	What type of area did you live when you were a child?

Identify Some Answers

Scale	Description
1	Rural (countryside)
2	Suburban
3	Urban (town, city)

Column	Identifications
gender	What is your gender?

Identify Some Answers

Scale	Description
1	Male
2	Female
3	Other

Column	Identifications
engnat	Is English your native language?

Identify Some Answers

Scale	Description
1	Yes
2	No

Column	Identifications
age	How many years old are you?

Column	Identifications
hand	What hand do you use to write with?

Identify Some Answers

Scale	Description
1	Right
2	Left
3	Both

Column	Identifications
religion	What is your religion?

Identify Some Answers

Scale	Description
1	Agnostic
2	Atheist
3	Buddhist
4	Christian (Catholic)
5	Christian (Mormon)
6	Christian (Protestant)
7	Christian (Other)
8	Hindu
9	Jewish
10	Muslim
11	Sikh
12	Other

Column	Identifications
orientation	What is your sexual orientation?

Identify Some Answers

Scale	Description
1	Heterosexual
2	Bisexual
3	Homosexual
4	Asexual
5	Other

Column	Identifications
race	What is your race?

Identify Some Answers

Scale	Description
10	Asian
20	Arab
30	Black
40	Indigenous Australian
50	Native American
60	White
70	Other

Column	Identifications
voted	Have you voted in a national election in the past year?

Identify Some Answers

Scale	Description
1	Yes
2	No

Column	Identifications
married	What is your marital status?

Identify Some Answers

Scale	Description
1	Never married
2	Currently married
3	Previously married

Column	Identifications
familysize	Including you, how many children did your mother have?

Column	Identifications
major	If you attended a university, what was your major (e.g., "psychology", "English", "civil engineering")?

The following values were derived from technical information"

Column	Identifications
country	ISO country code of where the user connected from.

Column	Identifications
screensize	The type of screen.

Identify Some Answers

Scale	Description
1	Device with small screen (phone, etc)
2	Device with big screen (laptop, desktop, etc)

Column	Identifications
uniquenetworklocation	One survey or multiple surveys.

Identify Some Answers

Scale	Description
1	Only one survey from the user's specific network in the dataset
2	Multiple surveys submitted from the network of this user

HINT !!!

(2 does not necessarily imply duplicate records for an individual, as it could be different students at a single school or different memebers of the same household; and even if 1 there still could be duplicate records from a single individual e.g. if they took it once on their wifi and once on their phone)

Column	Identifications
source	How the user found the test.

Identify Some Answers

Scale	Description
1	From the front page of the site hosting the survey
2	From Google

0	Other or unknown

Column	Identifications
age group	Detect which age group that user contains

Identify Some Answers

Scale	Description
1	Under or up to 10 years of age
2	Between 10 & 16
3	Between 17 & 21

(2) Import libraries

In [1]:
```
1 !pip install --upgrade tensorflow
```

```
Requirement already satisfied: tensorflow in c:\users\scs\anaconda3\lib\site-
packages (2.15.0)

WARNING: Ignoring invalid distribution -mpy (c:\users\scs\anaconda3\lib\site-
packages)
WARNING: Ignoring invalid distribution -umpy (c:\users\scs\anaconda3\lib\site
-packages)
WARNING: Ignoring invalid distribution -pencv-python (c:\users\scs\anaconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution - (c:\users\scs\anaconda3\lib\site-pac
kages)
WARNING: Ignoring invalid distribution -mpy (c:\users\scs\anaconda3\lib\site-
packages)
WARNING: Ignoring invalid distribution -umpy (c:\users\scs\anaconda3\lib\site
-packages)
WARNING: Ignoring invalid distribution -pencv-python (c:\users\scs\anaconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution - (c:\users\scs\anaconda3\lib\site-pac
kages)
WARNING: Ignoring invalid distribution -mpy (c:\users\scs\anaconda3\lib\site-
packages)
WARNING: Ignoring invalid distribution -umpy (c:\users\scs\anaconda3\lib\site
-packages)
```

```
Requirement already satisfied: tensorflow-intel==2.15.0 in c:\users\scs\anaco
nda3\lib\site-packages (from tensorflow) (2.15.0)
Requirement already satisfied: wrapt<1.15,>=1.11.0 in c:\users\scs\anaconda3
\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (1.12.1)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in c:\users\scs\anaconda3
\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (1.60.0)
Requirement already satisfied: google-pasta>=0.1.1 in c:\users\scs\anaconda3
\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (0.2.0)
Requirement already satisfied: setuptools in c:\users\scs\anaconda3\lib\site-
packages (from tensorflow-intel==2.15.0->tensorflow) (61.2.0)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=
4.21.4,!=4.21.5,<5.0.0dev,>=3.20.3 in c:\users\scs\anaconda3\lib\site-package
s (from tensorflow-intel==2.15.0->tensorflow) (4.23.4)
Requirement already satisfied: absl-py>=1.0.0 in c:\users\scs\anaconda3\lib\s
ite-packages (from tensorflow-intel==2.15.0->tensorflow) (2.0.0)
Requirement already satisfied: ml-dtypes~=0.2.0 in c:\users\scs\anaconda3\lib
\site-packages (from tensorflow-intel==2.15.0->tensorflow) (0.2.0)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in c:\use
rs\scs\anaconda3\lib\site-packages (from tensorflow-intel==2.15.0->tensorflo
w) (0.31.0)
Requirement already satisfied: astunparse>=1.6.0 in c:\users\scs\anaconda3\li
b\site-packages (from tensorflow-intel==2.15.0->tensorflow) (1.6.3)
Requirement already satisfied: typing-extensions>=3.6.6 in c:\users\scs\anaco
nda3\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (4.9.0)
Requirement already satisfied: libclang>=13.0.0 in c:\users\scs\anaconda3\lib
\site-packages (from tensorflow-intel==2.15.0->tensorflow) (16.0.6)
Requirement already satisfied: h5py>=2.9.0 in c:\users\scs\anaconda3\lib\site
-packages (from tensorflow-intel==2.15.0->tensorflow) (3.6.0)
Requirement already satisfied: tensorflow-estimator<2.16,>=2.15.0 in c:\users
\scs\anaconda3\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow)
(2.15.0)
Requirement already satisfied: six>=1.12.0 in c:\users\scs\anaconda3\lib\site
-packages (from tensorflow-intel==2.15.0->tensorflow) (1.16.0)
Requirement already satisfied: termcolor>=1.1.0 in c:\users\scs\anaconda3\lib
\site-packages (from tensorflow-intel==2.15.0->tensorflow) (2.4.0)
Requirement already satisfied: flatbuffers>=23.5.26 in c:\users\scs\anaconda3
\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (23.5.26)
Collecting numpy<2.0.0,>=1.23.5
  Using cached numpy-1.26.4-cp39-cp39-win_amd64.whl (15.8 MB)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in c:\user
s\scs\anaconda3\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow)
(0.5.4)
Requirement already satisfied: tensorboard<2.16,>=2.15 in c:\users\scs\anacon
da3\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (2.15.1)
Requirement already satisfied: keras<2.16,>=2.15.0 in c:\users\scs\anaconda3
\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (2.15.0)
Requirement already satisfied: opt-einsum>=2.3.2 in c:\users\scs\anaconda3\li
b\site-packages (from tensorflow-intel==2.15.0->tensorflow) (3.3.0)
Requirement already satisfied: packaging in c:\users\scs\anaconda3\lib\site-p
ackages (from tensorflow-intel==2.15.0->tensorflow) (21.3)
Requirement already satisfied: wheel<1.0,>=0.23.0 in c:\users\scs\anaconda3\l
ib\site-packages (from astunparse>=1.6.0->tensorflow-intel==2.15.0->tensorflo
w) (0.37.1)
Requirement already satisfied: google-auth<3,>=1.6.3 in c:\users\scs\anaconda
3\lib\site-packages (from tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->
tensorflow) (2.25.2)
```

```
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in c:\us
ers\scs\anaconda3\lib\site-packages (from tensorboard<2.16,>=2.15->tensorflow
-intel==2.15.0->tensorflow) (0.7.2)
Requirement already satisfied: google-auth-oauthlib<2,>=0.5 in c:\users\scs\a
naconda3\lib\site-packages (from tensorboard<2.16,>=2.15->tensorflow-intel==
2.15.0->tensorflow) (1.2.0)
Requirement already satisfied: markdown>=2.6.8 in c:\users\scs\anaconda3\lib
\site-packages (from tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tenso
rflow) (3.3.4)
Requirement already satisfied: werkzeug>=1.0.1 in c:\users\scs\anaconda3\lib
\site-packages (from tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tenso
rflow) (2.0.3)
Requirement already satisfied: requests<3,>=2.21.0 in c:\users\scs\anaconda3
\lib\site-packages (from tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->t
ensorflow) (2.27.1)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in c:\users\scs\anacond
a3\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard<2.16,>=2.15->te
nsorflow-intel==2.15.0->tensorflow) (4.2.2)
Requirement already satisfied: rsa<5,>=3.1.4 in c:\users\scs\anaconda3\lib\si
te-packages (from google-auth<3,>=1.6.3->tensorboard<2.16,>=2.15->tensorflow-
intel==2.15.0->tensorflow) (4.7.2)
Requirement already satisfied: pyasn1-modules>=0.2.1 in c:\users\scs\anaconda
3\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard<2.16,>=2.15->ten
sorflow-intel==2.15.0->tensorflow) (0.2.8)
Requirement already satisfied: requests-oauthlib>=0.7.0 in c:\users\scs\anaco
nda3\lib\site-packages (from google-auth-oauthlib<2,>=0.5->tensorboard<2.16,>
=2.15->tensorflow-intel==2.15.0->tensorflow) (1.3.1)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in c:\users\scs\anaconda3
\lib\site-packages (from pyasn1-modules>=0.2.1->google-auth<3,>=1.6.3->tensor
board<2.16,>=2.15->tensorflow-intel==2.15.0->tensorflow) (0.4.8)
Requirement already satisfied: charset-normalizer~=2.0.0 in c:\users\scs\anac
onda3\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.16,>=2.15->t
ensorflow-intel==2.15.0->tensorflow) (2.0.4)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\scs\anaconda3\l
ib\site-packages (from requests<3,>=2.21.0->tensorboard<2.16,>=2.15->tensorfl
ow-intel==2.15.0->tensorflow) (2023.11.17)
Requirement already satisfied: idna<4,>=2.5 in c:\users\scs\anaconda3\lib\sit
e-packages (from requests<3,>=2.21.0->tensorboard<2.16,>=2.15->tensorflow-int
el==2.15.0->tensorflow) (3.3)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in c:\users\scs\anaconda
3\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.16,>=2.15->tenso
rflow-intel==2.15.0->tensorflow) (1.26.9)
Requirement already satisfied: oauthlib>=3.0.0 in c:\users\scs\anaconda3\lib
\site-packages (from requests-oauthlib>=0.7.0->google-auth-oauthlib<2,>=0.5->
tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tensorflow) (3.2.2)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in c:\users\scs\anaco
nda3\lib\site-packages (from packaging->tensorflow-intel==2.15.0->tensorflow)
(3.0.4)
Installing collected packages: numpy
  Attempting uninstall: numpy
    Found existing installation: numpy 1.22.4
    Uninstalling numpy-1.22.4:
      Successfully uninstalled numpy-1.22.4
Successfully installed numpy-1.26.4
```

```
WARNING: Ignoring invalid distribution -pencv-python (c:\users\scs\anaconda3
\lib\site-packages)
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kages)
    WARNING: Ignoring invalid distribution -mpy (c:\users\scs\anaconda3\lib\s
ite-packages)
    WARNING: Ignoring invalid distribution -umpy (c:\users\scs\anaconda3\lib
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    WARNING: Ignoring invalid distribution -pencv-python (c:\users\scs\anacon
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WARNING: Ignoring invalid distribution -pencv-python (c:\users\scs\anaconda3
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WARNING: Ignoring invalid distribution - (c:\users\scs\anaconda3\lib\site-pac
kages)
ERROR: pip's dependency resolver does not currently take into account all the
packages that are installed. This behaviour is the source of the following de
pendency conflicts.
daal4py 2021.5.0 requires daal==2021.4.0, which is not installed.
ydata-profiling 4.6.4 requires numpy<1.26,>=1.16.0, but you have numpy 1.26.4
which is incompatible.
scipy 1.7.3 requires numpy<1.23.0,>=1.16.5, but you have numpy 1.26.4 which i
s incompatible.
WARNING: Ignoring invalid distribution -mpy (c:\users\scs\anaconda3\lib\site-
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WARNING: Ignoring invalid distribution -pencv-python (c:\users\scs\anaconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution - (c:\users\scs\anaconda3\lib\site-pac
kages)
```

In [2]:

```
# !pip install ydata-profiling
```

In [1]:

```
# for analysis
import numpy as np
import pandas as pd

# for creating a demo profiling
from ydata_profiling import ProfileReport
from ydata_profiling.utils.cache import cache_file

# for visulization
import matplotlib.pyplot as plt
import seaborn as sns

# for mathimatical & random operations
import math
import random

# for framework operations
import tensorflow as tf
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.activations import relu, linear, softmax
from tensorflow.keras.optimizers import Adam, SGD, RMSprop
from tensorflow.keras.models import save_model as sm
from tensorflow.keras.models import load_model as lm

# for data rescalling
from sklearn.preprocessing import MinMaxScaler

# for spiliting data
from sklearn.model_selection import train_test_split,cross_val_score

# for buiding model
from lazypredict.Supervised import LazyClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC, SVR

#for evaluation
from sklearn.metrics import confusion_matrix, plot_confusion_matrix,accura

#for check high bais & high variance
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit

#for saving model
import pickle
import joblib
```

```
c:\Users\scs\anaconda3\lib\site-packages\scipy\__init__.py:146: UserWarning:
A NumPy version >=1.16.5 and <1.23.0 is required for this version of SciPy (d
etected version 1.26.4
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

(3) Reading & Showing Data

In [4]:
```
pd.set_option('display.max_columns',172)
path = 'D:/COURSES/Programming Language/python/data_scince_track/projects/I
df = pd.read_csv(path, delimiter='\t')
pd.set_option('display.max_columns',172)
df
```

Out[4]:

	Q1A	Q1I	Q1E	Q2A	Q2I	Q2E	Q3A	Q3I	Q3E	Q4A	Q4I	Q4E	Q5A	Q5I	Q5E	Q
0	4	28	3890	4	25	2122	2	16	1944	4	8	2044	4	34	2153	
1	4	2	8118	1	36	2890	2	35	4777	3	28	3090	4	10	5078	
2	3	7	5784	1	33	4373	4	41	3242	1	13	6470	4	11	3927	
3	2	23	5081	3	11	6837	2	37	5521	1	27	4556	3	28	3269	
4	2	36	3215	2	13	7731	3	5	4156	4	10	2802	4	2	5628	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
39770	2	31	3287	1	5	2216	3	29	3895	2	37	2767	3	39	1745	
39771	3	14	4792	4	41	2604	3	15	2668	4	33	4609	3	17	2434	
39772	2	1	25147	1	4	4555	2	14	3388	1	27	2753	1	6	5455	
39773	3	36	4286	1	34	2736	2	10	5968	2	20	5655	3	9	2296	
39774	2	28	32251	1	22	3317	2	4	11734	1	19	4659	4	32	4236	

39775 rows × 172 columns

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

Out[5]:
```
Index(['Q1A', 'Q1I', 'Q1E', 'Q2A', 'Q2I', 'Q2E', 'Q3A', 'Q3I', 'Q3E', 'Q4A',
       ...
       'screensize', 'uniquenetworklocation', 'hand', 'religion',
       'orientation', 'race', 'voted', 'married', 'familysize', 'major'],
      dtype='object', length=172)
```

In [6]:
```
print(f'The Shape of DataFrame: {df.shape}')
print(f'The Number of Rows: {df.shape[0]}')
print(f'The Number of Columns: {df.shape[1]}')
```

```
The Shape of DataFrame: (39775, 172)
The Number of Rows: 39775
The Number of Columns: 172
```

In [7]:
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39775 entries, 0 to 39774
Columns: 172 entries, Q1A to major
dtypes: int64(170), object(2)
memory usage: 52.2+ MB
```

In [8]:
```
1 df.select_dtypes(include=['object']).columns
```

Out[8]:
```
Index(['country', 'major'], dtype='object')
```

In [9]:
```
1 description = df[['age', 'familysize']].describe()
2 np.ceil(description)
```

Out[9]:

	age	familysize
count	39775.00	39775.00
mean	24.00	4.00
std	22.00	3.00
min	13.00	0.00
25%	18.00	2.00
50%	21.00	3.00
75%	25.00	4.00
max	1998.00	133.00

In [10]:
```
1 np.array(df)
```

Out[10]:
```
array([[4, 28, 3890, ..., 1, 2, nan],
       [4, 2, 8118, ..., 1, 4, nan],
       [3, 7, 5784, ..., 1, 3, nan],
       ...,
       [2, 1, 25147, ..., 2, 3, 'Computer Science'],
       [3, 36, 4286, ..., 1, 2, 'History'],
       [2, 28, 32251, ..., 1, 4, 'Cognitive Science']], dtype=object)
```

In [11]:
```
1 df.ndim
```

Out[11]:
```
2
```

(3) Data Analysis

In [12]:
```
# report=ProfileReport(df, title="Demo Profiling", explorative=True)
# report.to_file("D:/COURSES/Programming Language/python/data_scince_track/
```

In [13]:
```
def get_value_counts_per_column_range(df, column_range):
    value_counts_per_column = {}
    for column in df.columns[column_range]:
        value_counts = df[column].value_counts()
        value_counts_per_column[column] = value_counts
    return value_counts_per_column
```

In [14]:
```
def plot_null_values(df, columns_to_check):
    plt.figure(figsize=(20, 10))
    null_values = df[columns_to_check].isnull()
    print("Null values in the specified columns:")
    print(null_values)
    sns.heatmap(null_values, yticklabels=False, cmap='viridis')
    plt.xticks(ticks=range(len(columns_to_check)), labels=columns_to_check
    plt.title('Null Values Distribution in Dataframe')
    plt.show()
```

In [15]:
```
def sum_null_values(dataframe, columns_to_sum=None):
    nan_sum_per_column = {}
    if columns_to_sum is None:
        columns_to_sum = dataframe.columns
    for column in columns_to_sum:
        nan_sum = dataframe[column].isna().sum()
        nan_sum_per_column[column] = nan_sum
    return nan_sum_per_column
```

Part One (Q) :

NOTE !!!

THe Columns of Part One(Q) That Contain I & E that Determine The Position of Question and The Time That The User Taken to Solve are not Needed for The User so That We Will Drop Them.

In [16]:
```
removedcolumns=[f'Q{i}I' for i in range(1,43)]
removedcolumns.extend([f'Q{i}E' for i in range(1,43)])
df=df.drop(removedcolumns ,axis=1)
df.head()
```

Out[16]:

	Q1A	Q2A	Q3A	Q4A	Q5A	Q6A	Q7A	Q8A	Q9A	Q10A	Q11A	Q12A	Q13A	Q14A	Q15A
0	4	4	2	4	4	4	4	4	2	1	4	4	4	4	4
1	4	1	2	3	4	4	3	4	3	2	2	2	4	4	3
2	3	1	4	1	4	3	1	3	2	4	2	1	4	1	4
3	2	3	2	1	3	3	4	2	3	3	2	1	1	4	2
4	2	2	3	4	4	2	4	4	4	3	2	4	4	4	4

In [17]:
```
df.shape
```

Out[17]: (39775, 88)

In [18]:

```
for i in df.columns[0:42]:
    unique_values = df[i].unique()
    print(f"Unique values in {i}: {unique_values}")
```

```
Unique values in Q1A: [4 3 2 1]
Unique values in Q2A: [4 1 3 2]
Unique values in Q3A: [2 4 3 1]
Unique values in Q4A: [4 3 1 2]
Unique values in Q5A: [4 3 1 2]
Unique values in Q6A: [4 3 2 1]
Unique values in Q7A: [4 3 1 2]
Unique values in Q8A: [4 3 2 1]
Unique values in Q9A: [2 3 4 1]
Unique values in Q10A: [1 2 4 3]
Unique values in Q11A: [4 2 1 3]
Unique values in Q12A: [4 2 1 3]
Unique values in Q13A: [4 1 2 3]
Unique values in Q14A: [4 1 3 2]
Unique values in Q15A: [4 3 2 1]
Unique values in Q16A: [4 3 2 1]
Unique values in Q17A: [3 4 2 1]
Unique values in Q18A: [4 2 1 3]
Unique values in Q19A: [3 1 2 4]
Unique values in Q20A: [3 1 2 4]
Unique values in Q21A: [1 2 4 3]
Unique values in Q22A: [4 3 1 2]
Unique values in Q23A: [4 1 2 3]
Unique values in Q24A: [4 2 1 3]
Unique values in Q25A: [4 2 1 3]
Unique values in Q26A: [4 3 1 2]
Unique values in Q27A: [4 3 2 1]
Unique values in Q28A: [3 4 1 2]
Unique values in Q29A: [4 3 2 1]
Unique values in Q30A: [2 3 4 1]
Unique values in Q31A: [4 2 3 1]
Unique values in Q32A: [4 3 1 2]
Unique values in Q33A: [2 3 1 4]
Unique values in Q34A: [3 2 4 1]
Unique values in Q35A: [4 2 3 1]
Unique values in Q36A: [4 3 1 2]
Unique values in Q37A: [1 4 2 3]
Unique values in Q38A: [2 4 1 3]
Unique values in Q39A: [4 2 3 1]
Unique values in Q40A: [3 1 2 4]
Unique values in Q41A: [4 2 1 3]
Unique values in Q42A: [4 2 3 1]
```

In [19]:

```
selected_column_range = range(0, 42)
result = get_value_counts_per_column_range(df, selected_column_range)
for column, counts in result.items():
    print(f"Value counts for {column}:\n{counts}\n")
```

```
Value counts for Q1A:
2    13320
4    10393
3     9958
1     6104
Name: Q1A, dtype: int64

Value counts for Q2A:
1    14385
2    11504
4     7351
3     6535
Name: Q2A, dtype: int64

Value counts for Q3A:
2    14062
1    11563
3     7744
4     6406
Name: Q3A, dtype: int64

Value counts for Q4A:
1    17757
2    11128
3     6005
4     4885
Name: Q4A, dtype: int64

Value counts for Q5A:
2    12794
4     9788
3     9179
1     8014
Name: Q5A, dtype: int64

Value counts for Q6A:
2    13291
4     9649
3     9512
1     7323
Name: Q6A, dtype: int64

Value counts for Q7A:
1    18092
2    11333
3     5594
4     4756
Name: Q7A, dtype: int64

Value counts for Q8A:
2    13471
3     9241
4     8977
1     8086
Name: Q8A, dtype: int64

Value counts for Q9A:
```

```
2    11788
4    11734
3     9709
1     6544
Name: Q9A, dtype: int64

Value counts for Q10A:
2    11007
1    10625
4    10274
3     7869
Name: Q10A, dtype: int64

Value counts for Q11A:
4    13598
2    11136
3     9898
1     5143
Name: Q11A, dtype: int64

Value counts for Q12A:
2    12601
3     9439
1     9326
4     8409
Name: Q12A, dtype: int64

Value counts for Q13A:
4    13922
2    11200
3     9007
1     5646
Name: Q13A, dtype: int64

Value counts for Q14A:
2    12535
4    10842
3     8897
1     7501
Name: Q14A, dtype: int64

Value counts for Q15A:
1    19587
2    11262
3     5150
4     3776
Name: Q15A, dtype: int64

Value counts for Q16A:
2    11696
4    10579
1     8996
3     8504
Name: Q16A, dtype: int64

Value counts for Q17A:
4    13509
```

```
2     9800
1     8644
3     7822
Name: Q17A, dtype: int64

Value counts for Q18A:
2    12789
3     9277
4     9142
1     8567
Name: Q18A, dtype: int64

Value counts for Q19A:
1    18506
2    10370
4     5471
3     5428
Name: Q19A, dtype: int64

Value counts for Q20A:
1    11946
2    11489
4     8455
3     7885
Name: Q20A, dtype: int64

Value counts for Q21A:
1    12694
2    10308
4     9826
3     6947
Name: Q21A, dtype: int64

Value counts for Q22A:
2    14327
1     9448
3     8850
4     7150
Name: Q22A, dtype: int64

Value counts for Q23A:
1    25111
2     9139
3     3349
4     2176
Name: Q23A, dtype: int64

Value counts for Q24A:
2    13790
3     8919
1     8555
4     8511
Name: Q24A, dtype: int64

Value counts for Q25A:
1    13569
2    11924
```

```
3     7664
4     6618
Name: Q25A, dtype: int64

Value counts for Q26A:
2    11979
4    11573
3     9636
1     6587
Name: Q26A, dtype: int64

Value counts for Q27A:
2    12889
4    10634
3     9670
1     6582
Name: Q27A, dtype: int64

Value counts for Q28A:
1    12734
2    12495
3     7716
4     6830
Name: Q28A, dtype: int64

Value counts for Q29A:
2    12280
4    11338
3     9733
1     6424
Name: Q29A, dtype: int64

Value counts for Q30A:
2    12535
1    10000
3     8875
4     8365
Name: Q30A, dtype: int64

Value counts for Q31A:
2    14022
1     9254
3     8756
4     7743
Name: Q31A, dtype: int64

Value counts for Q32A:
2    14441
3     9653
4     7919
1     7762
Name: Q32A, dtype: int64

Value counts for Q33A:
2    13146
3     9498
1     9095
```

```
4     8036
Name: Q33A, dtype: int64

Value counts for Q34A:
4    13064
2    10268
1     8677
3     7766
Name: Q34A, dtype: int64

Value counts for Q35A:
2    15373
1     9317
3     8810
4     6275
Name: Q35A, dtype: int64

Value counts for Q36A:
1    12517
2    12042
4     7974
3     7242
Name: Q36A, dtype: int64

Value counts for Q37A:
1    11580
2    11362
4     9605
3     7228
Name: Q37A, dtype: int64

Value counts for Q38A:
1    12551
4    10746
2     9797
3     6681
Name: Q38A, dtype: int64

Value counts for Q39A:
2    14405
3     9657
4     8040
1     7673
Name: Q39A, dtype: int64

Value counts for Q40A:
4    12219
2    10788
3     9109
1     7659
Name: Q40A, dtype: int64

Value counts for Q41A:
1    17323
2    11617
3     5693
4     5142
```

```
Name: Q41A, dtype: int64

Value counts for Q42A:
2    12886
4    11304
3    10014
1     5571
Name: Q42A, dtype: int64
```

In [20]:

```
columns_to_check = df.columns[0:42]
plot_null_values(df, columns_to_check)
```

Null values in the specified columns:

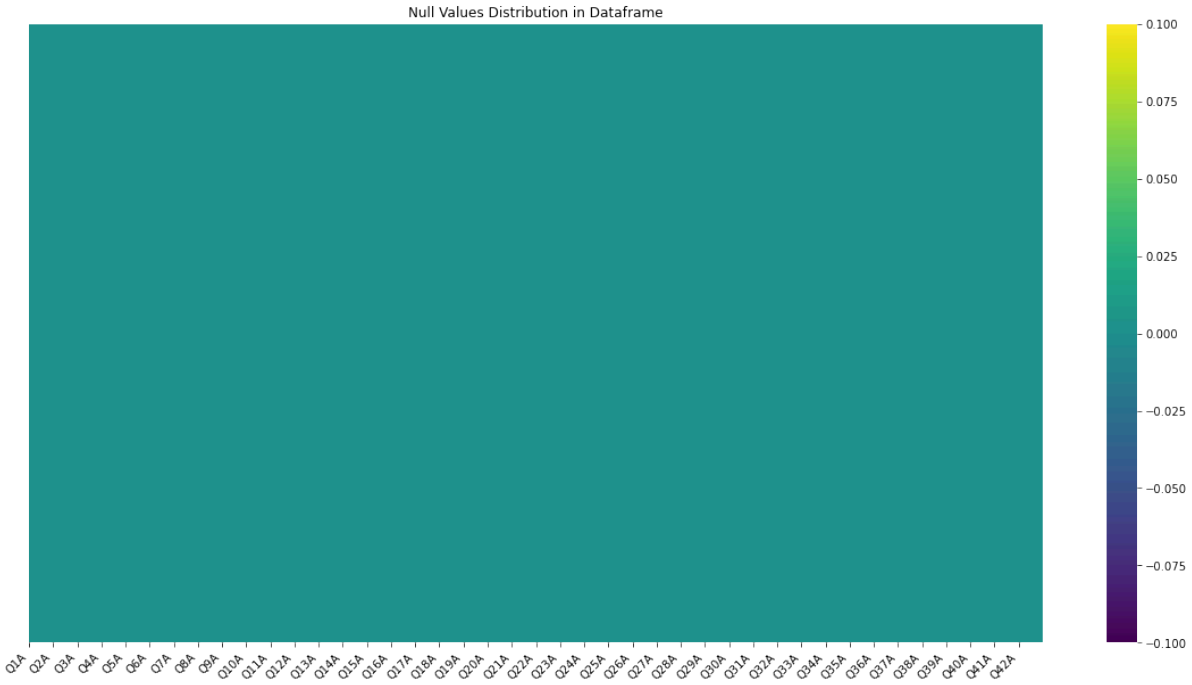
	Q1A	Q2A	Q3A	Q4A	Q5A	Q6A	Q7A	Q8A	Q9A	Q10A
0	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...
39770	False	False	False	False	False	False	False	False	False	False
39771	False	False	False	False	False	False	False	False	False	False
39772	False	False	False	False	False	False	False	False	False	False
39773	False	False	False	False	False	False	False	False	False	False
39774	False	False	False	False	False	False	False	False	False	False

	Q11A	Q12A	Q13A	Q14A	Q15A	Q16A	Q17A	Q18A	Q19A	Q20A
0	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...
39770	False	False	False	False	False	False	False	False	False	False
39771	False	False	False	False	False	False	False	False	False	False
39772	False	False	False	False	False	False	False	False	False	False
39773	False	False	False	False	False	False	False	False	False	False
39774	False	False	False	False	False	False	False	False	False	False

	Q21A	Q22A	Q23A	Q24A	Q25A	Q26A	Q27A	Q28A	Q29A	Q30A
0	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...
39770	False	False	False	False	False	False	False	False	False	False
39771	False	False	False	False	False	False	False	False	False	False
39772	False	False	False	False	False	False	False	False	False	False
39773	False	False	False	False	False	False	False	False	False	False
39774	False	False	False	False	False	False	False	False	False	False

	Q31A	Q32A	Q33A	Q34A	Q35A	Q36A	Q37A	Q38A	Q39A	Q40A
0	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...
39770	False	False	False	False	False	False	False	False	False	False
39771	False	False	False	False	False	False	False	False	False	False
39772	False	False	False	False	False	False	False	False	False	False
39773	False	False	False	False	False	False	False	False	False	False
39774	False	False	False	False	False	False	False	False	False	False

```
       Q41A   Q42A
0     False  False
1     False  False
2     False  False
3     False  False
4     False  False
...     ...    ...
39770 False  False
39771 False  False
39772 False  False
39773 False  False
39774 False  False

[39775 rows x 42 columns]
```

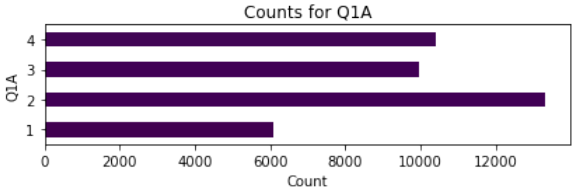


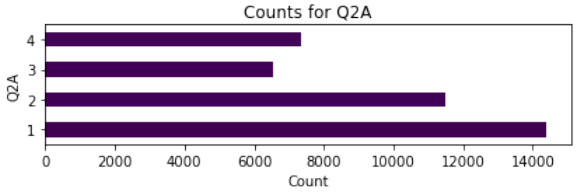
In [21]:
```
columns_to_sum = df.columns[0:42]
sum_null_values(df,columns_to_sum)
```

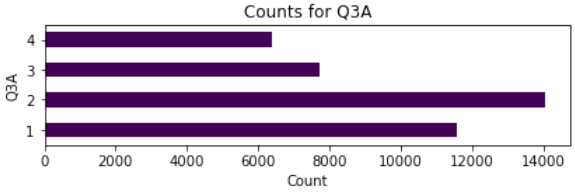
Out[21]:
```
{'Q1A': 0,
 'Q2A': 0,
 'Q3A': 0,
 'Q4A': 0,
 'Q5A': 0,
 'Q6A': 0,
 'Q7A': 0,
 'Q8A': 0,
 'Q9A': 0,
 'Q10A': 0,
 'Q11A': 0,
 'Q12A': 0,
 'Q13A': 0,
 'Q14A': 0,
 'Q15A': 0,
 'Q16A': 0,
 'Q17A': 0,
 'Q18A': 0,
 'Q19A': 0,
 'Q20A': 0,
 'Q21A': 0,
 'Q22A': 0,
 'Q23A': 0,
 'Q24A': 0,
 'Q25A': 0,
 'Q26A': 0,
 'Q27A': 0,
 'Q28A': 0,
 'Q29A': 0,
 'Q30A': 0,
 'Q31A': 0,
 'Q32A': 0,
 'Q33A': 0,
 'Q34A': 0,
 'Q35A': 0,
 'Q36A': 0,
 'Q37A': 0,
 'Q38A': 0,
 'Q39A': 0,
 'Q40A': 0,
 'Q41A': 0,
 'Q42A': 0}
```

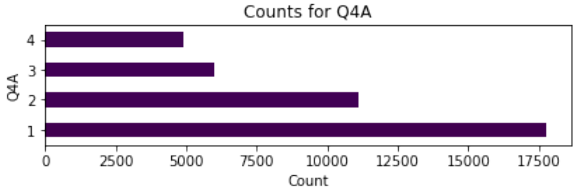
In [22]:

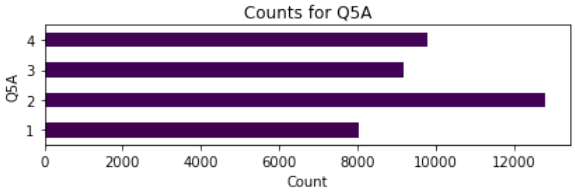
```
columns_to_plot = df.columns[0:42]
num_columns = 2
num_rows = math.ceil(len(columns_to_plot) / num_columns)
fig, axes = plt.subplots(nrows=num_rows, ncols=num_columns, figsize=(12, 2
for i, column in enumerate(columns_to_plot):
    row = i // num_columns
    col = i % num_columns
    ax = axes[row, col]
    counts = df[column].value_counts().sort_index()
    colors = plt.cm.viridis.colors[:len(counts)]
    counts.plot(kind='barh', ax=ax, color=colors)
    ax.set_title(f'Counts for {column}')
    ax.set_ylabel(column)
    ax.set_xlabel('Count')
for i in range(len(columns_to_plot), num_rows * num_columns):
    fig.delaxes(axes.flatten()[i])
plt.tight_layout()
plt.show()
```

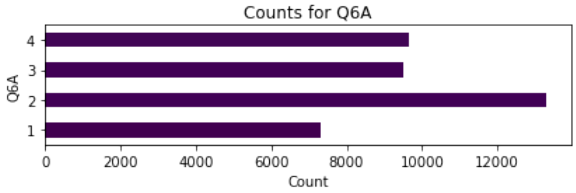

Counts for Q1A
Q1A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
Count

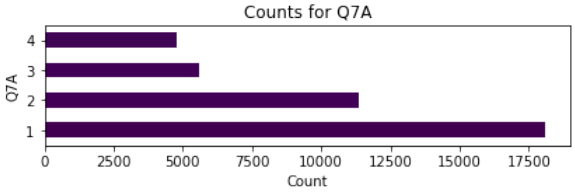

Counts for Q2A
Q2A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
14000
Count

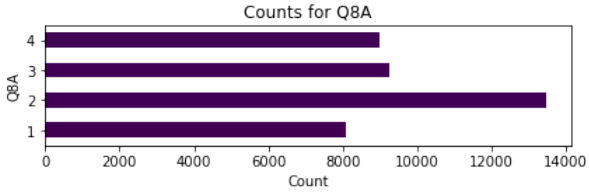

Counts for Q3A
Q3A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
14000
Count

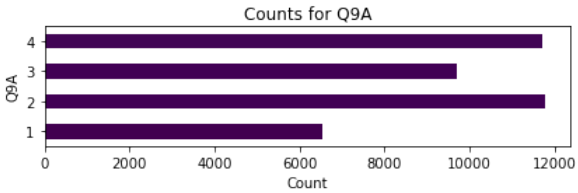

Counts for Q4A
Q4A
4
3
2
1
0
2500
5000
7500
10000
12500
15000
17500
Count

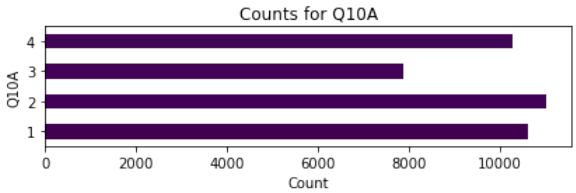

Counts for Q5A
Q5A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
Count

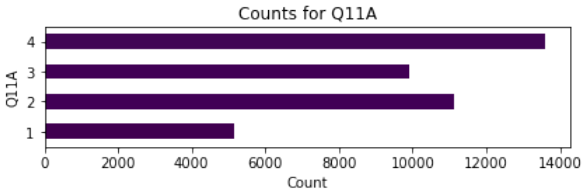

Counts for Q6A
Q6A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
Count

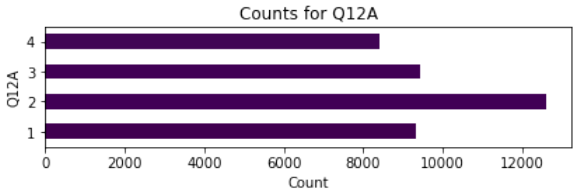

Counts for Q7A
Q7A
4
3
2
1
0
2500
5000
7500
10000
12500
15000
17500
Count

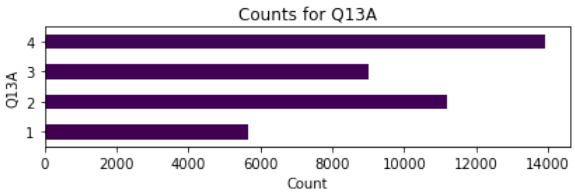

Counts for Q8A
Q8A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
14000
Count

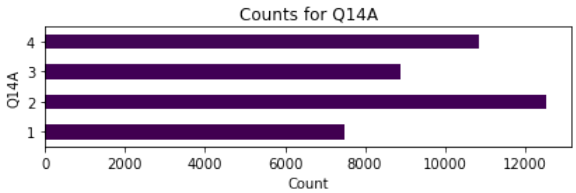

Counts for Q9A
Q9A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
Count

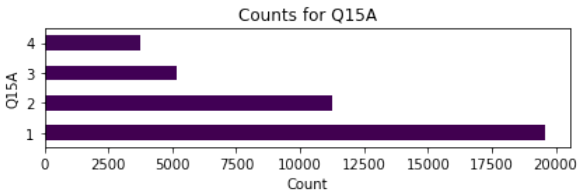

Counts for Q10A
Q10A
4
3
2
1
0
2000
4000
6000
8000
10000
Count

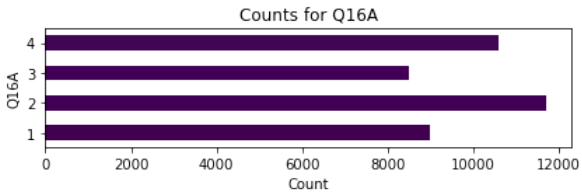

Counts for Q11A
Q11A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
14000
Count

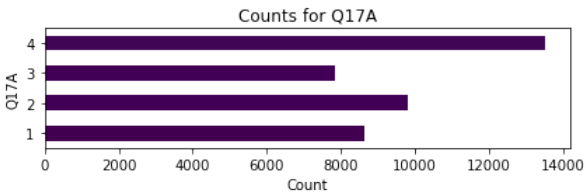

Counts for Q12A
Q12A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
Count

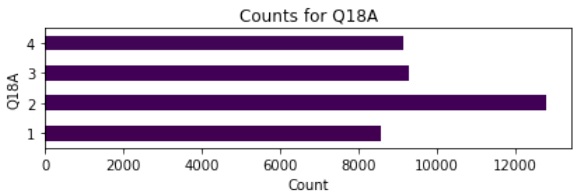

Counts for Q13A
Q13A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
14000
Count

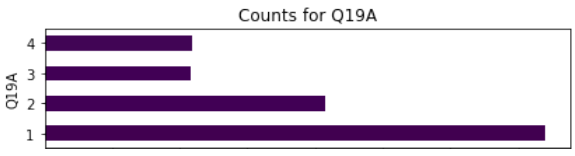

Counts for Q14A
Q14A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
Count

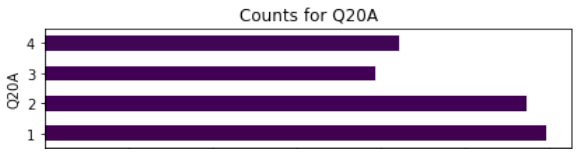

Counts for Q15A
Q15A
4
3
2
1
0
2500
5000
7500
10000
12500
15000
17500
20000
Count

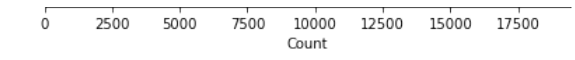

Counts for Q16A
Q16A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
Count

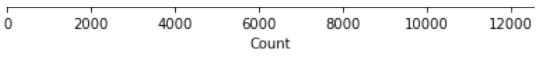

Counts for Q17A
Q17A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
14000
Count

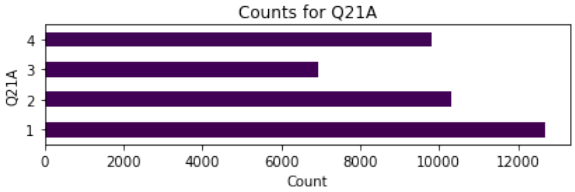

Counts for Q18A
Q18A
4
3
2
1
0
2000
4000
6000
8000
10000
12000
Count

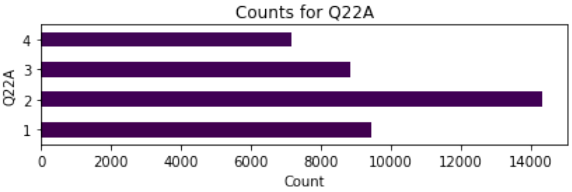

Counts for Q19A
Q19A
4
3
2
1

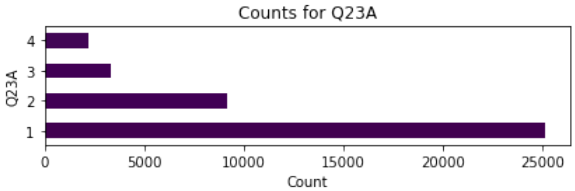

Counts for Q20A
Q20A
4
3
2
1

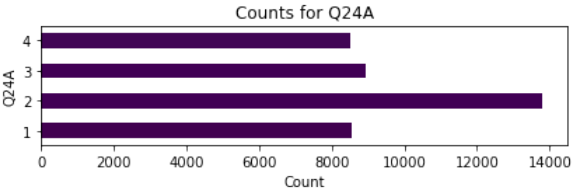

0 2500 5000 7500 10000 12500 15000 17500
Count

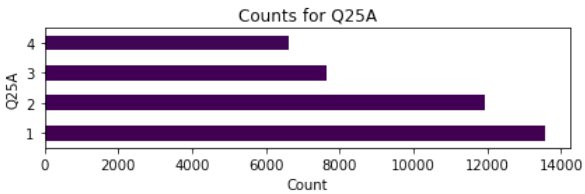

0 2000 4000 6000 8000 10000 12000
Count

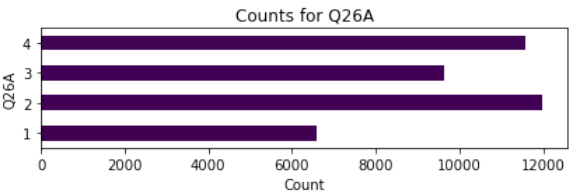

Counts for Q21A
Q21A
4 3 2 1
0 2000 4000 6000 8000 10000 12000
Count

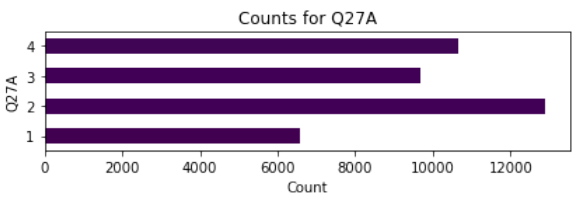

Counts for Q22A
Q22A
4 3 2 1
0 2000 4000 6000 8000 10000 12000 14000
Count

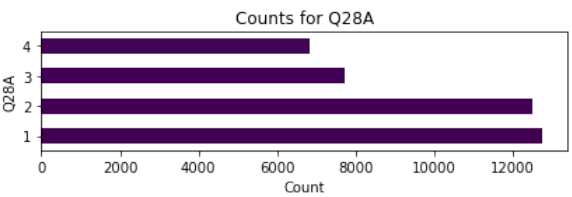

Counts for Q23A
Q23A
4 3 2 1
0 5000 10000 15000 20000 25000
Count

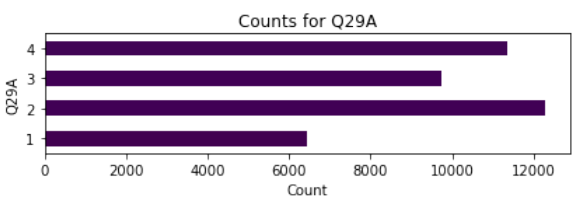

Counts for Q24A
Q24A
4 3 2 1
0 2000 4000 6000 8000 10000 12000 14000
Count

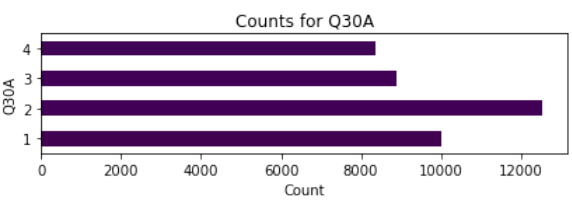

Counts for Q25A
Q25A
4 3 2 1
0 2000 4000 6000 8000 10000 12000 14000
Count

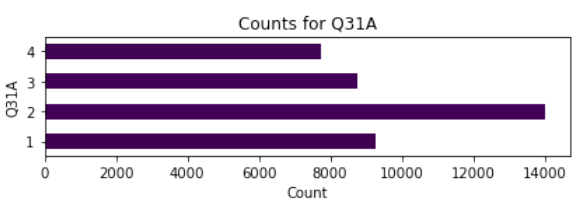

Counts for Q26A
Q26A
4 3 2 1
0 2000 4000 6000 8000 10000 12000
Count

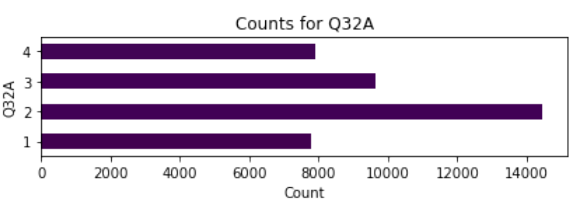

Counts for Q27A
Q27A
4 3 2 1
0 2000 4000 6000 8000 10000 12000
Count

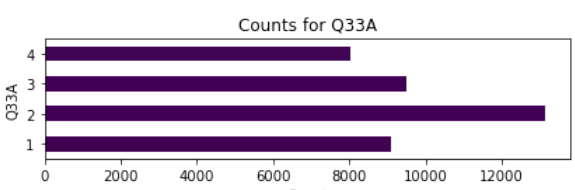

Counts for Q28A
Q28A
4 3 2 1
0 2000 4000 6000 8000 10000 12000
Count

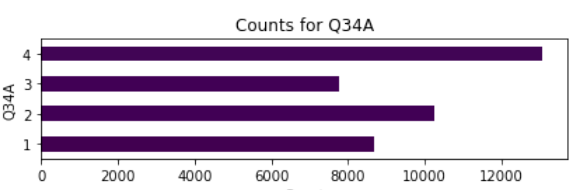

Counts for Q29A
Q29A
4 3 2 1
0 2000 4000 6000 8000 10000 12000
Count

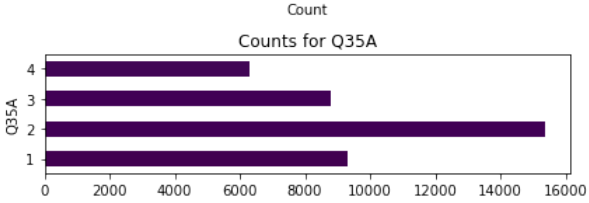

Counts for Q30A
Q30A
4 3 2 1
0 2000 4000 6000 8000 10000 12000
Count

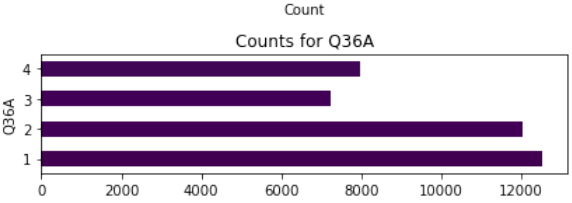

Counts for Q31A
Q31A
4 3 2 1
0 2000 4000 6000 8000 10000 12000 14000
Count

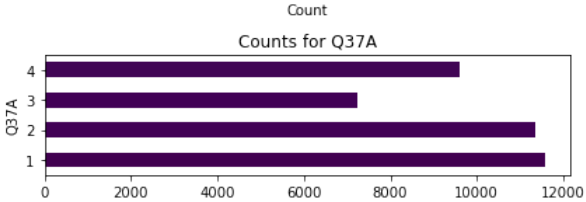

Counts for Q32A
Q32A
4 3 2 1
0 2000 4000 6000 8000 10000 12000 14000
Count

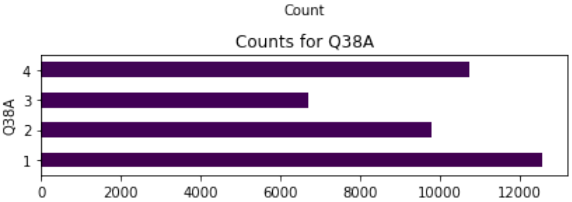

Counts for Q33A
Q33A
4 3 2 1
0 2000 4000 6000 8000 10000 12000
Count

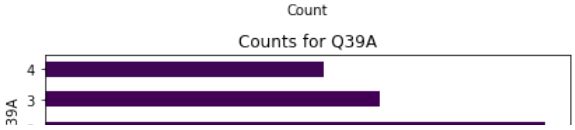

Counts for Q34A
Q34A
4 3 2 1
0 2000 4000 6000 8000 10000 12000
Count

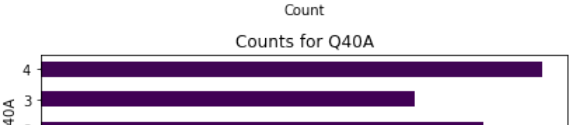

Counts for Q35A
Q35A
4 3 2 1
0 2000 4000 6000 8000 10000 12000 14000 16000
Count

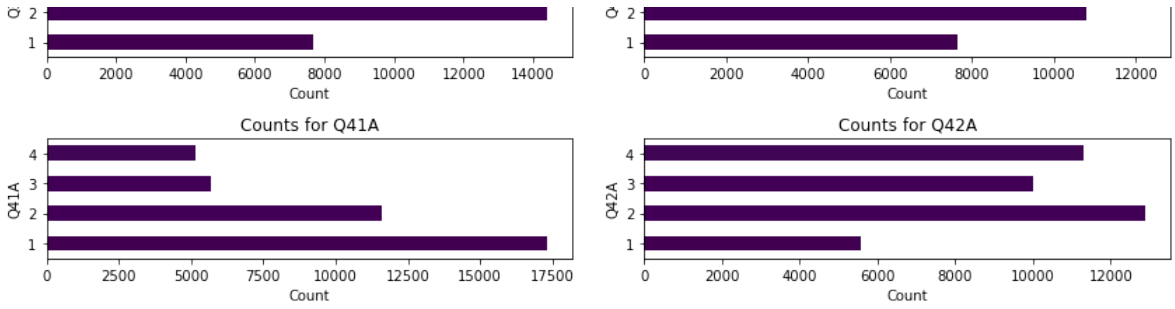

Counts for Q36A
Q36A
4 3 2 1
0 2000 4000 6000 8000 10000 12000
Count


Counts for Q37A
Q37A
4 3 2 1
0 2000 4000 6000 8000 10000 12000
Count


Counts for Q38A
Q38A
4 3 2 1
0 2000 4000 6000 8000 10000 12000
Count

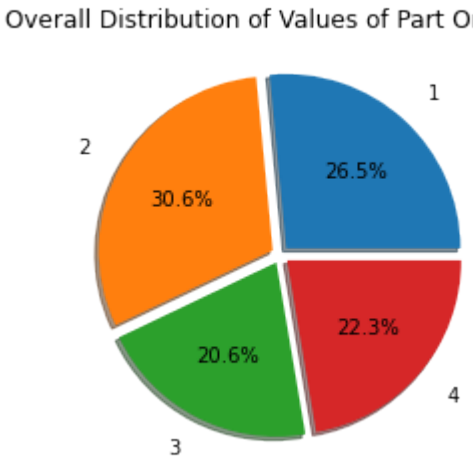

Counts for Q39A
4 3


Counts for Q40A
4 3



In [23]:

```
1 columns_to_plot = df.columns[0:42]
2 unique_values = [1, 2, 3, 4]
3 overall_value_counts = df[columns_to_plot].stack().value_counts()
4 total_count = overall_value_counts.sum()
5 overall_percentages = [overall_value_counts.get(val, 0) / total_count * 10
6 plt.pie(overall_percentages, labels=unique_values, explode=[0.05,0.05,0.05
7 plt.title('Overall Distribution of Values of Part One(QA)')
8 plt.show()
```

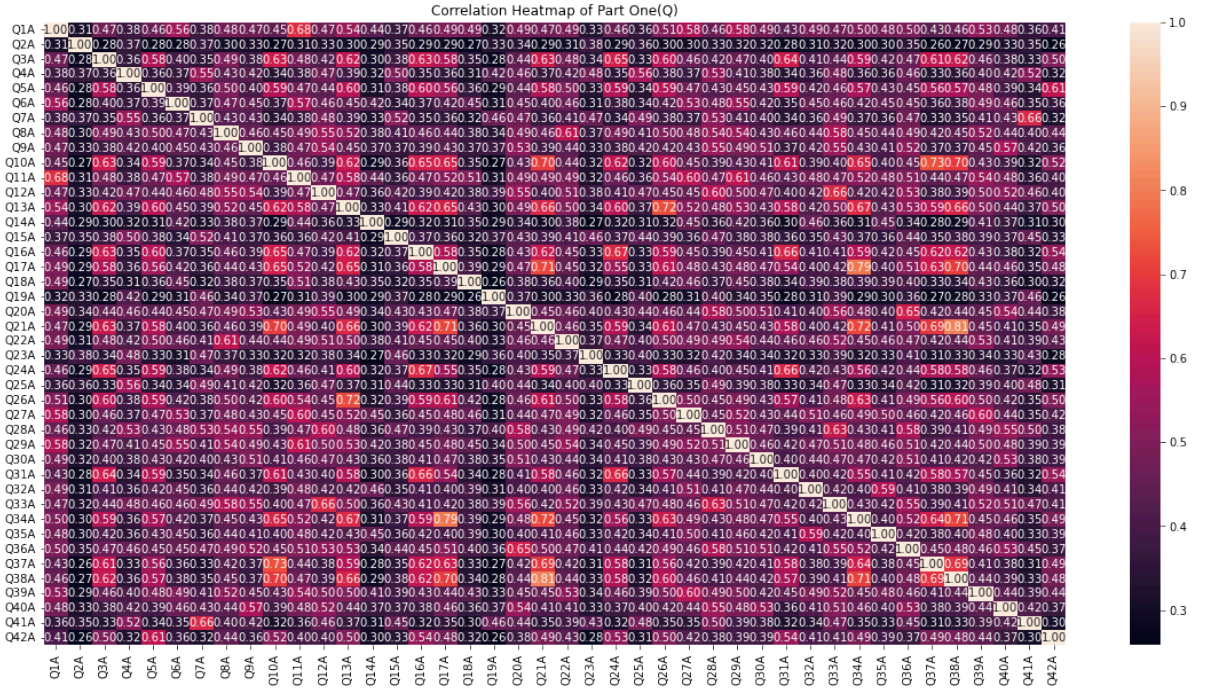


In [24]:

```
1 selected_columns = df.iloc[:, 0:43]
```

In [25]:

```
plt.figure(figsize=(20, 10))
sns.heatmap(selected_columns.corr(), annot=True, fmt=".2f")
plt.title('Correlation Heatmap of Part One(Q)')
plt.show()
```



Part Two(other durations were also recorded & measured on the server's side) :

NOTE !!!

THe Columns of Part Two That measured on the server's side, User Dont Use Them so We Will Dropped **introelapse** & **testelapse** & **surveyelapse**

In [26]:

```
columns_to_drop = ['introelapse', 'testelapse', 'surveyelapse']

if all(col in df.columns for col in columns_to_drop):
    df = df.drop(columns=columns_to_drop, axis=1)
else:
    print("'introelapse', 'testelapse', or 'surveyelapse' not found in Data
```

In [27]:
```
1 df.shape[1]
```

Out[27]: 85

In [28]:
```
1 df
```

Out[28]:

	Q1A	Q2A	Q3A	Q4A	Q5A	Q6A	Q7A	Q8A	Q9A	Q10A	Q11A	Q12A	Q13A	Q14A	Q
0	4	4	2	4	4	4	4	4	2	1	4	4	4	4	
1	4	1	2	3	4	4	3	4	3	2	2	2	4	4	
2	3	1	4	1	4	3	1	3	2	4	2	1	4	1	
3	2	3	2	1	3	3	4	2	3	3	2	1	1	4	
4	2	2	3	4	4	2	4	4	4	3	2	4	4	4	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
39770	2	1	3	2	3	2	1	3	1	4	2	2	4	2	
39771	3	4	3	4	3	4	4	4	3	4	4	4	4	4	
39772	2	1	2	1	1	1	1	1	2	1	1	1	2	1	
39773	3	1	2	2	3	3	3	4	3	1	3	3	4	4	
39774	2	1	2	1	4	2	1	1	1	1	3	1	3	1	

39775 rows × 85 columns

Part Three (TIPI) :

In [29]:
```
1 df.columns.get_loc('TIPI1')
```

Out[29]: 44

In [30]:
```
1 df.columns.get_loc('TIPI10')
```

Out[30]: 53

In [31]:

```
for i in df.columns[44:54]:
    unique_values = df[i].unique()
    print(f"Unique values in {i}: {unique_values}")
```

```
Unique values in TIPI1: [1 6 2 7 5 3 4 0]
Unique values in TIPI2: [5 1 6 4 7 3 2 0]
Unique values in TIPI3: [7 4 2 3 6 5 1 0]
Unique values in TIPI4: [7 2 4 6 1 5 0 3]
Unique values in TIPI5: [7 5 6 3 2 1 4 0]
Unique values in TIPI6: [7 4 6 5 2 1 3 0]
Unique values in TIPI7: [7 5 6 1 4 3 2 0]
Unique values in TIPI8: [5 7 1 6 2 3 4 0]
Unique values in TIPI9: [1 3 6 5 2 7 4 0]
Unique values in TIPI10: [1 5 2 3 7 4 6 0]
```

In [32]:

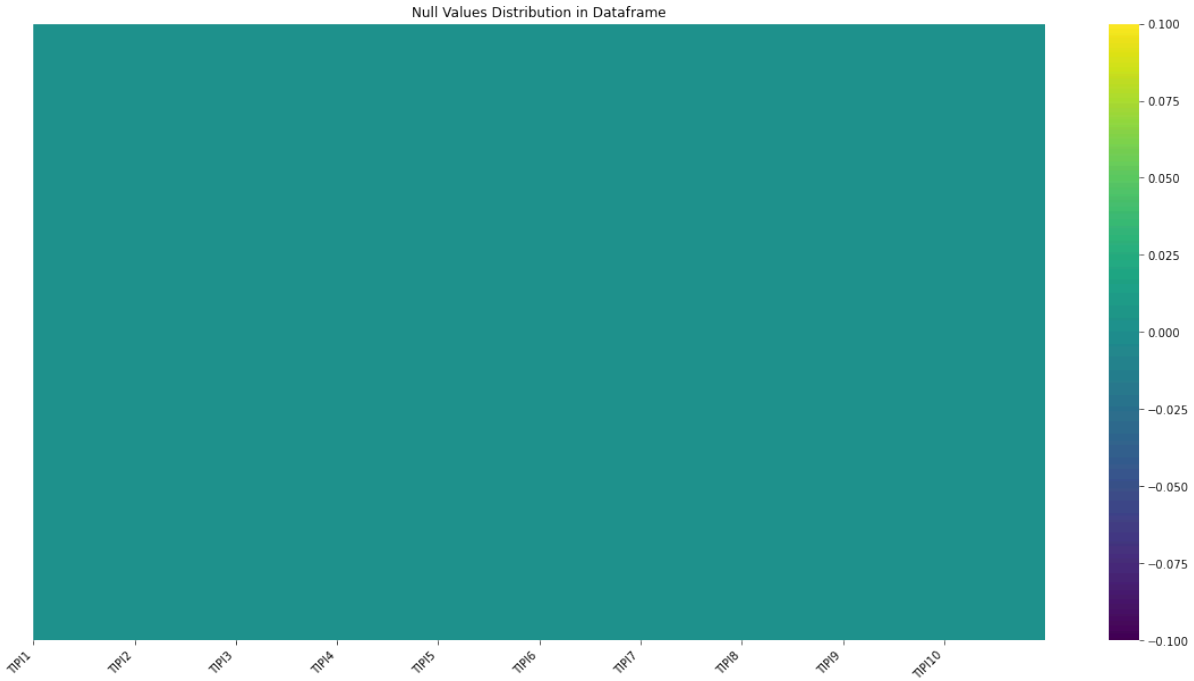
```
selected_column_range = range(44, 54)
result = get_value_counts_per_column_range(df, selected_column_range)
for column, counts in result.items():
    print(f"Value counts for {column}:\n{counts}\n")
```

```
Value counts for TIPI1:
5    8420
1    6229
6    6046
4    5877
2    5603
3    4633
7    2482
0     485
Name: TIPI1, dtype: int64

Value counts for TIPI2:
5    10373
6     6990
4     6171
3     4326
2     4040
1     3985
7     3320
0      570
Name: TIPI2, dtype: int64

Value counts for TIPI3:
6    10230
5     9121
7     6242
4     4516
3     3981
2     2843
1     2252
0      590
Name: TIPI3, dtype: int64

Value counts for TIPI4:
7    11360
6     9561
5     8751
4     2720
2     2444
3     2434
1     2042
0      463
Name: TIPI4, dtype: int64

Value counts for TIPI5:
6    9697
5    9525
7    7682
4    5140
3    3341
2    2226
1    1647
0     517
Name: TIPI5, dtype: int64

Value counts for TIPI6:
7    9626
```

```
6    8094
5    7733
4    4943
3    3475
2    2748
1    2666
0     490
Name: TIPI6, dtype: int64

Value counts for TIPI7:
6    10997
7    10007
5     9097
4     4421
3     2270
2     1367
1     1015
0      601
Name: TIPI7, dtype: int64

Value counts for TIPI8:
5    9300
6    6369
7    5841
4    4577
3    4446
2    4445
1    4138
0     659
Name: TIPI8, dtype: int64

Value counts for TIPI9:
4    6837
3    6819
2    6401
5    6250
1    5507
6    4943
7    2591
0     427
Name: TIPI9, dtype: int64

Value counts for TIPI10:
4    7665
5    6653
3    6184
2    5714
1    5404
6    4106
7    3494
0     555
Name: TIPI10, dtype: int64
```

In [33]:
```
columns_to_check = df.columns[44:54]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       TIPI1  TIPI2  TIPI3  TIPI4  TIPI5  TIPI6  TIPI7  TIPI8  TIPI9  TIPI10
0      False  False  False  False  False  False  False  False  False   False
1      False  False  False  False  False  False  False  False  False   False
2      False  False  False  False  False  False  False  False  False   False
3      False  False  False  False  False  False  False  False  False   False
4      False  False  False  False  False  False  False  False  False   False
...      ...    ...    ...    ...    ...    ...    ...    ...    ...     ...
39770  False  False  False  False  False  False  False  False  False   False
39771  False  False  False  False  False  False  False  False  False   False
39772  False  False  False  False  False  False  False  False  False   False
39773  False  False  False  False  False  False  False  False  False   False
39774  False  False  False  False  False  False  False  False  False   False

[39775 rows x 10 columns]
```

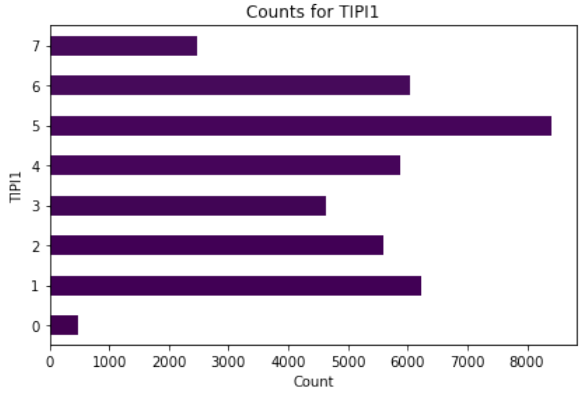


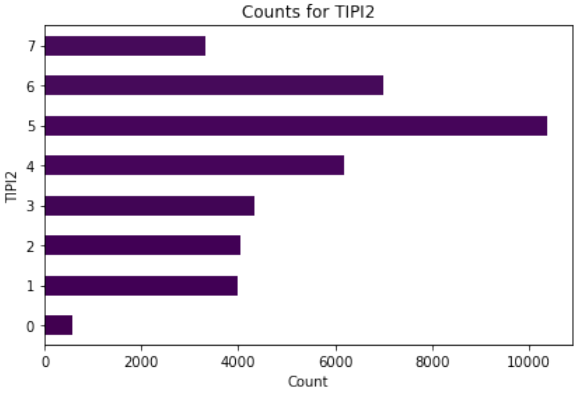
In [34]:
```
columns_to_sum = df.columns[44:54]
sum_null_values(df,columns_to_sum)
```

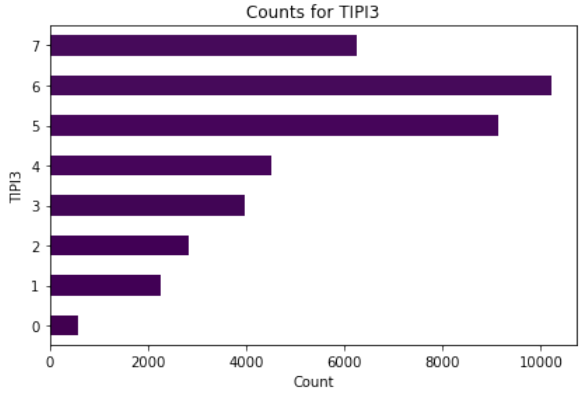
Out[34]:
```
{'TIPI1': 0,
 'TIPI2': 0,
 'TIPI3': 0,
 'TIPI4': 0,
 'TIPI5': 0,
 'TIPI6': 0,
 'TIPI7': 0,
 'TIPI8': 0,
 'TIPI9': 0,
 'TIPI10': 0}
```

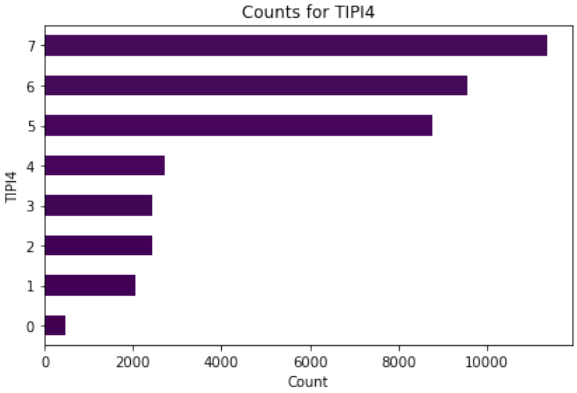
In [35]:

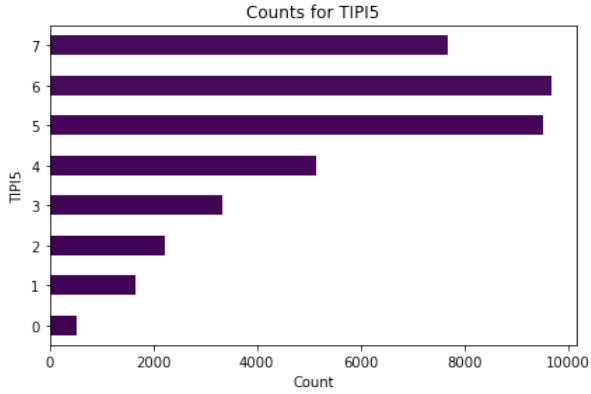
```
columns_to_plot = df.columns[44:54]
num_columns = 2
num_rows = math.ceil(len(columns_to_plot) / num_columns)
fig, axes = plt.subplots(nrows=num_rows, ncols=num_columns, figsize=(12, 4
for i, column in enumerate(columns_to_plot):
    row = i // num_columns
    col = i % num_columns
    ax = axes[row, col]
    counts = df[column].value_counts().sort_index()
    colors = plt.cm.viridis.colors[:len(counts)]
    counts.plot(kind='barh', ax=ax, color=colors)
    ax.set_title(f'Counts for {column}')
    ax.set_ylabel(column)
    ax.set_xlabel('Count')
for i in range(len(columns_to_plot), num_rows * num_columns):
    fig.delaxes(axes.flatten()[i])
plt.tight_layout()
plt.show()
```

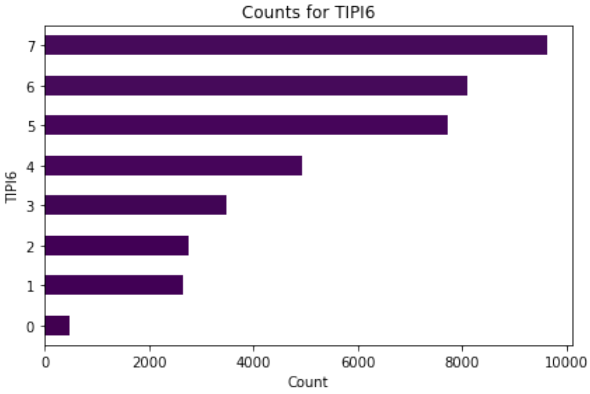

Counts for TIPI1
TIPI1
Count

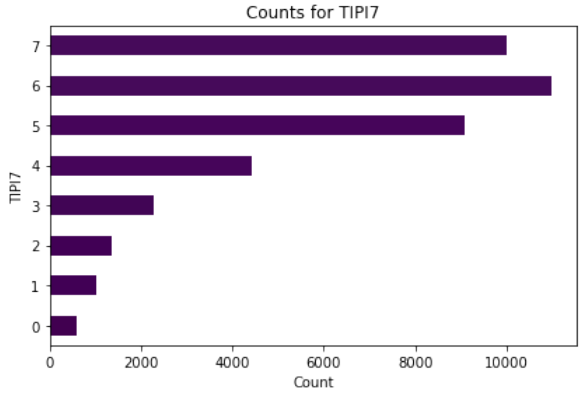

Counts for TIPI2
TIPI2
Count

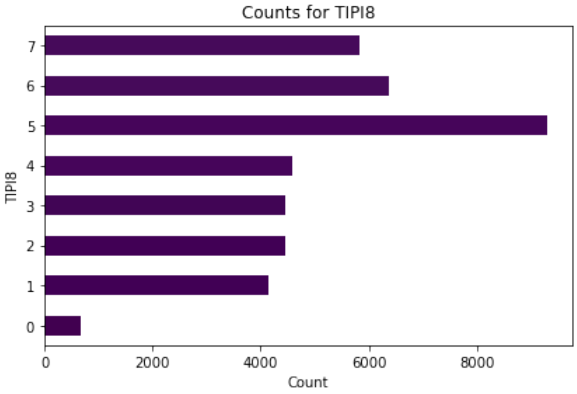

Counts for TIPI3
TIPI3
Count

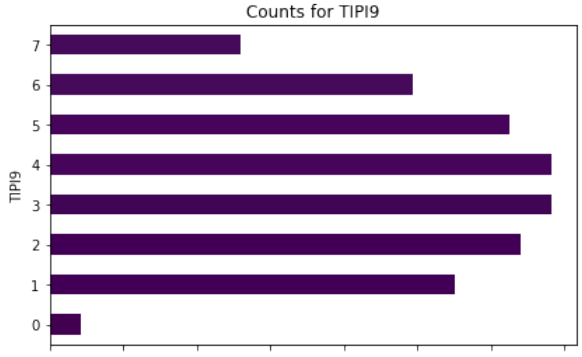

Counts for TIPI4
TIPI4
Count

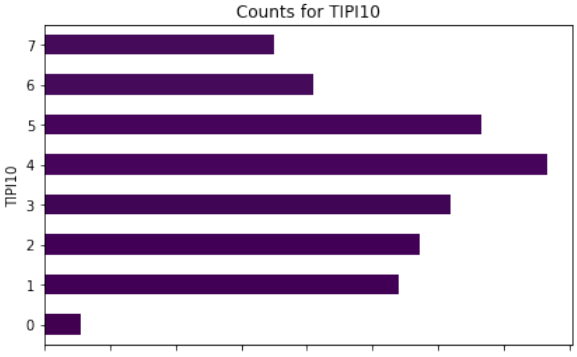

Counts for TIPI5
TIPI5
Count

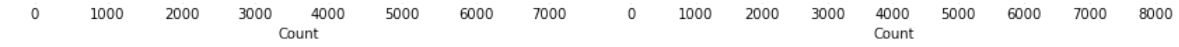

Counts for TIPI6
TIPI6
Count


Counts for TIPI7
TIPI7
Count


Counts for TIPI8
TIPI8
Count

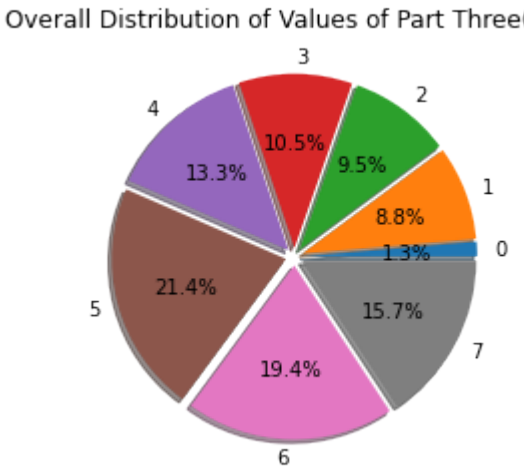

Counts for TIPI9
TIPI9


Counts for TIPI10
TIPI10



In [36]:

```
columns_to_plot = df.columns[44:54]
unique_values = [0, 1, 2, 3, 4, 5, 6, 7]
overall_value_counts = df[columns_to_plot].stack().value_counts()
total_count = overall_value_counts.sum()
overall_percentages = [overall_value_counts.get(val, 0) / total_count * 10
explode = [0.05] * len(unique_values)
plt.pie(overall_percentages, labels=unique_values, explode=explode, autopc
plt.title('Overall Distribution of Values of Part Three(TIPI)')
plt.show()
```



In [37]:

```
def replace_zeros_with_max_frequency_inplace(df, column_range):
    for column in df.columns[column_range]:
        highest_frequency = df[column].value_counts().idxmax()
        df[column].replace(0, highest_frequency, inplace=True)
```

In [38]:

```
replace_zeros_with_max_frequency_inplace(df, range(44,54))
```

In [39]:

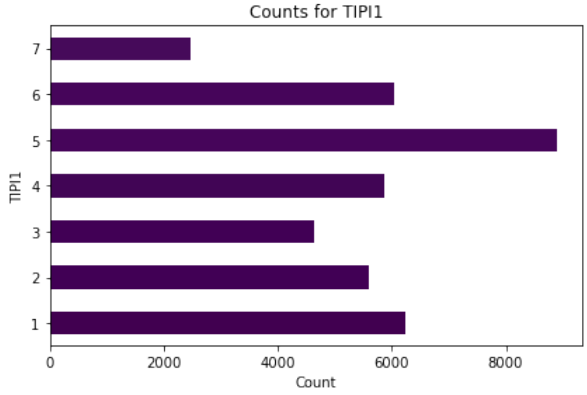
```
selected_column_range = range(44, 54)
result = get_value_counts_per_column_range(df, selected_column_range)
for column, counts in result.items():
    print(f"Value counts for {column}:\n{counts}\n")
```

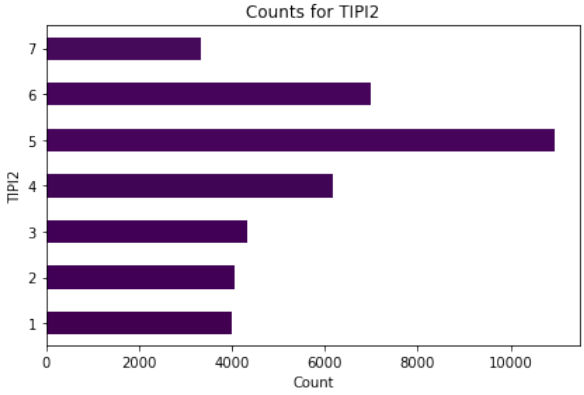
```
Value counts for TIPI1:
5    8905
1    6229
6    6046
4    5877
2    5603
3    4633
7    2482
Name: TIPI1, dtype: int64

Value counts for TIPI2:
5    10943
6     6990
4     6171
3     4326
2     4040
1     3985
7     3320
Name: TIPI2, dtype: int64

Value counts for TIPI3:
6    10820
5     9121
7     6242
4     4516
3     3981
2     2843
1     2252
Name: TIPI3, dtype: int64

Value counts for TIPI4:
7    11823
6     9561
5     8751
4     2720
2     2444
3     2434
1     2042
Name: TIPI4, dtype: int64

Value counts for TIPI5:
6    10214
5     9525
7     7682
4     5140
3     3341
2     2226
1     1647
Name: TIPI5, dtype: int64

Value counts for TIPI6:
7    10116
6     8094
5     7733
4     4943
3     3475
2     2748
```

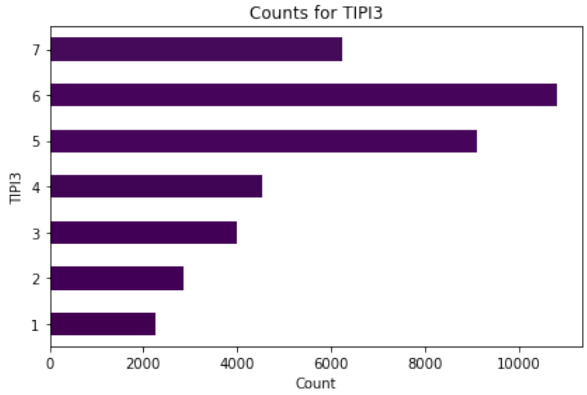
```
1     2666
Name: TIPI6, dtype: int64

Value counts for TIPI7:
6    11598
7    10007
5     9097
4     4421
3     2270
2     1367
1     1015
Name: TIPI7, dtype: int64

Value counts for TIPI8:
5    9959
6    6369
7    5841
4    4577
3    4446
2    4445
1    4138
Name: TIPI8, dtype: int64

Value counts for TIPI9:
4    7264
3    6819
2    6401
5    6250
1    5507
6    4943
7    2591
Name: TIPI9, dtype: int64

Value counts for TIPI10:
4    8220
5    6653
3    6184
2    5714
1    5404
6    4106
7    3494
Name: TIPI10, dtype: int64
```

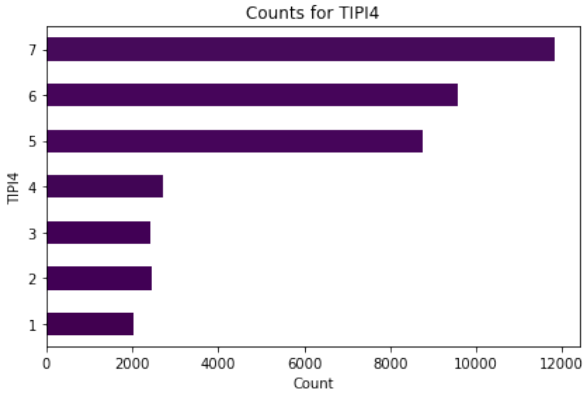
In [40]:

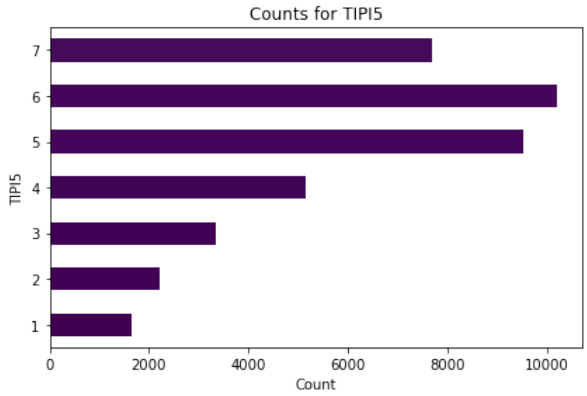
```
columns_to_plot = df.columns[44:54]
num_columns = 2
num_rows = math.ceil(len(columns_to_plot) / num_columns)
fig, axes = plt.subplots(nrows=num_rows, ncols=num_columns, figsize=(12, 4
for i, column in enumerate(columns_to_plot):
    row = i // num_columns
    col = i % num_columns
    ax = axes[row, col]
    counts = df[column].value_counts().sort_index()
    colors = plt.cm.viridis.colors[:len(counts)]
    counts.plot(kind='barh', ax=ax, color=colors)
    ax.set_title(f'Counts for {column}')
    ax.set_ylabel(column)
    ax.set_xlabel('Count')
for i in range(len(columns_to_plot), num_rows * num_columns):
    fig.delaxes(axes.flatten()[i])
plt.tight_layout()
plt.show()
```

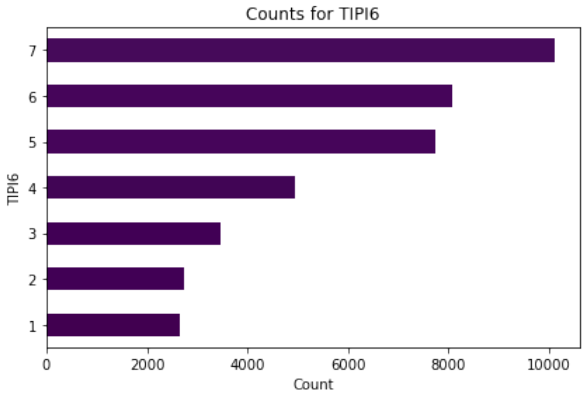

Counts for TIPI1
TIPI1
Count
0
2000
4000
6000
8000
1
2
3
4
5
6
7

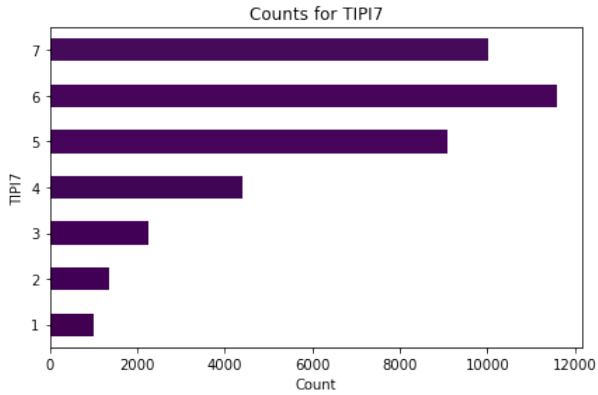

Counts for TIPI2
TIPI2
Count
0
2000
4000
6000
8000
10000
1
2
3
4
5
6
7

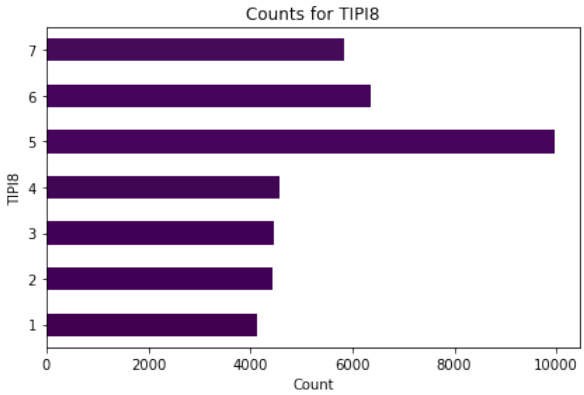

Counts for TIPI3
TIPI3
Count
0
2000
4000
6000
8000
10000
1
2
3
4
5
6
7

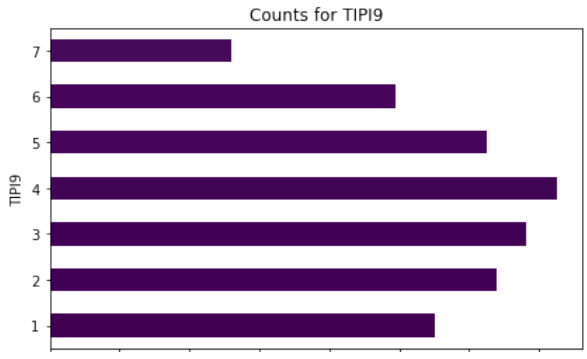

Counts for TIPI4
TIPI4
Count
0
2000
4000
6000
8000
10000
12000
1
2
3
4
5
6
7

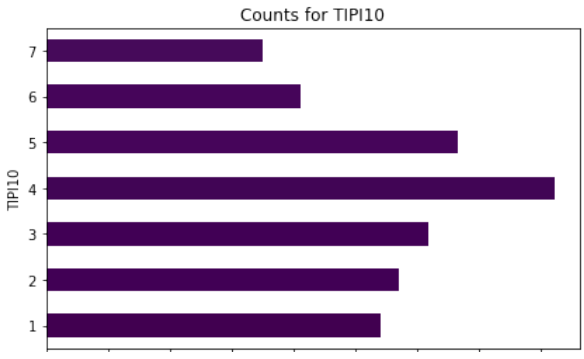

Counts for TIPI5
TIPI5
Count
0
2000
4000
6000
8000
10000
1
2
3
4
5
6
7


Counts for TIPI6
TIPI6
Count
0
2000
4000
6000
8000
10000
1
2
3
4
5
6
7


Counts for TIPI7
TIPI7
Count
0
2000
4000
6000
8000
10000
12000
1
2
3
4
5
6
7

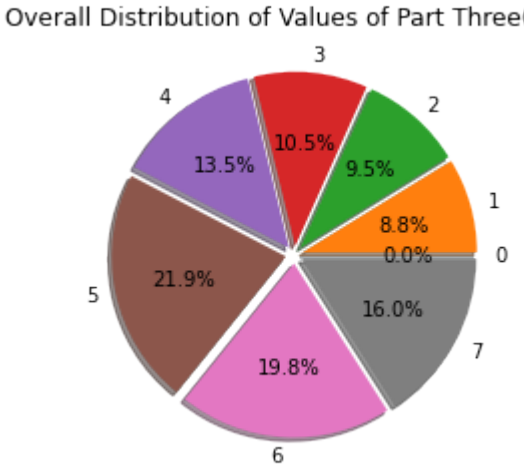

Counts for TIPI8
TIPI8
Count
0
2000
4000
6000
8000
10000
1
2
3
4
5
6
7


Counts for TIPI9
TIPI9
1
2
3
4
5
6
7


Counts for TIPI10
TIPI10
1
2
3
4
5
6
7

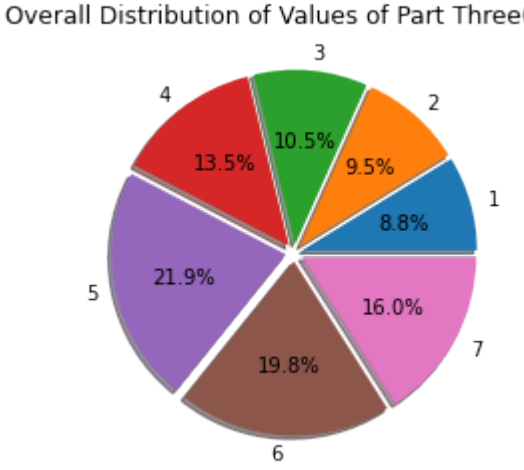
In [41]:

```
columns_to_plot = df.columns[44:54]
unique_values = [0, 1, 2, 3, 4, 5, 6, 7]
overall_value_counts = df[columns_to_plot].stack().value_counts()
total_count = overall_value_counts.sum()
overall_percentages = [overall_value_counts.get(val, 0) / total_count * 10
explode = [0.05] * len(unique_values)
plt.pie(overall_percentages, labels=unique_values, explode=explode, autopc
plt.title('Overall Distribution of Values of Part Three(TIPI)')
plt.show()
```



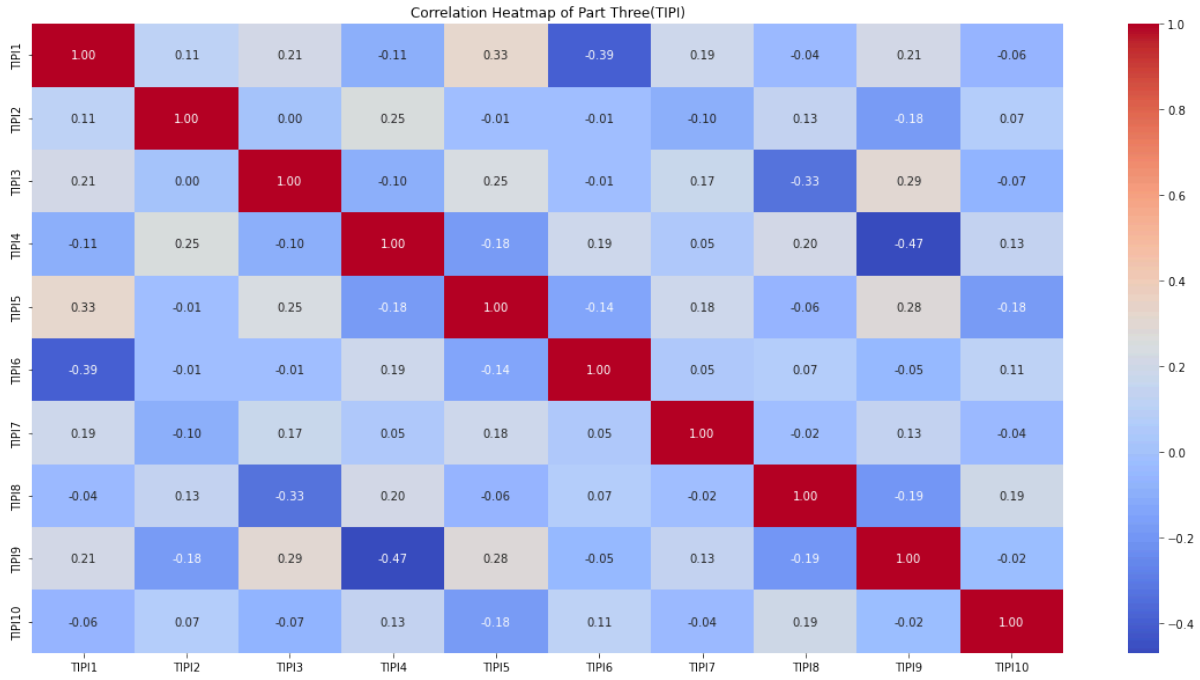
In [42]:

```
columns_to_plot = df.columns[44:54]
unique_values = [1, 2, 3, 4, 5, 6, 7]
overall_value_counts = df[columns_to_plot].stack().value_counts()
total_count = overall_value_counts.sum()
overall_percentages = [overall_value_counts.get(val, 0) / total_count * 10
explode = [0.05] * len(unique_values)
plt.pie(overall_percentages, labels=unique_values, explode=explode, autopc
plt.title('Overall Distribution of Values of Part Three(TIPI)')
plt.show()
```



In [43]:
```
selected_columns = df.iloc[:, 44:54]
```

In [44]:
```
plt.figure(figsize=(20, 10))
sns.heatmap(selected_columns.corr(), annot=True, cmap='coolwarm', fmt=".2f
plt.title('Correlation Heatmap of Part Three(TIPI)')
plt.show()
```



Part Four (VCL) :

In [45]:
```
df.columns.get_loc('VCL1')
```

Out[45]: 54

In [46]:
```
df.columns.get_loc('VCL16')
```

Out[46]: 69

In [47]:

```
for i in df.columns[54:70]:
    unique_values = df[i].unique()
    print(f"Unique values in {i}: {unique_values}")
```

```
Unique values in VCL1: [1 0]
Unique values in VCL2: [0 1]
Unique values in VCL3: [0 1]
Unique values in VCL4: [1 0]
Unique values in VCL5: [1 0]
Unique values in VCL6: [0 1]
Unique values in VCL7: [1 0]
Unique values in VCL8: [0 1]
Unique values in VCL9: [0 1]
Unique values in VCL10: [1 0]
Unique values in VCL11: [0 1]
Unique values in VCL12: [0 1]
Unique values in VCL13: [0 1]
Unique values in VCL14: [1 0]
Unique values in VCL15: [1 0]
Unique values in VCL16: [1 0]
```

In [48]:

```
selected_column_range = range(54, 70)
result = get_value_counts_per_column_range(df, selected_column_range)
for column, counts in result.items():
    print(f"Value counts for {column}:\n{counts}\n")
```

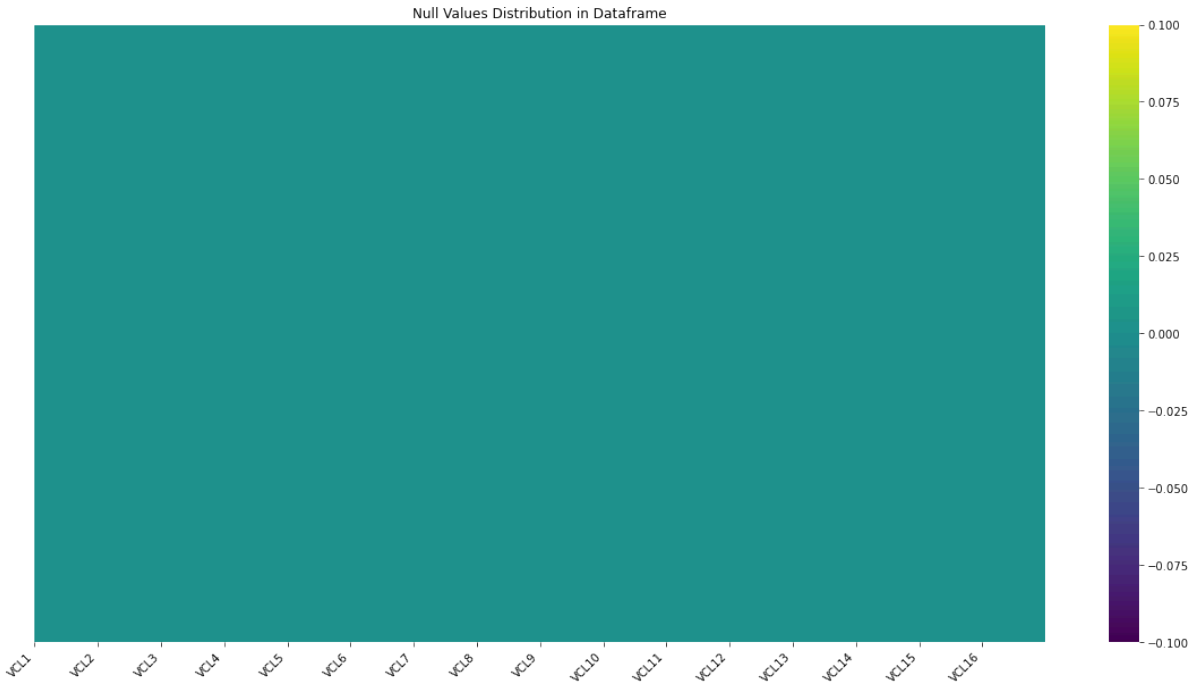
```
Value counts for VCL1:
1    32312
0     7463
Name: VCL1, dtype: int64

Value counts for VCL2:
1    23064
0    16711
Name: VCL2, dtype: int64

Value counts for VCL3:
0    33715
1     6060
Name: VCL3, dtype: int64

Value counts for VCL4:
1    34479
0     5296
Name: VCL4, dtype: int64

Value counts for VCL5:
1    27239
0    12536
Name: VCL5, dtype: int64

Value counts for VCL6:
0    38177
1     1598
Name: VCL6, dtype: int64

Value counts for VCL7:
0    36450
1     3325
Name: VCL7, dtype: int64

Value counts for VCL8:
0    33041
1     6734
Name: VCL8, dtype: int64

Value counts for VCL9:
0    38059
1     1716
Name: VCL9, dtype: int64

Value counts for VCL10:
1    34628
0     5147
Name: VCL10, dtype: int64

Value counts for VCL11:
0    36844
1     2931
Name: VCL11, dtype: int64

Value counts for VCL12:
0    36423
```

```
1     3352
Name: VCL12, dtype: int64

Value counts for VCL13:
0    28182
1    11593
Name: VCL13, dtype: int64

Value counts for VCL14:
1    22501
0    17274
Name: VCL14, dtype: int64

Value counts for VCL15:
1    33688
0     6087
Name: VCL15, dtype: int64

Value counts for VCL16:
1    37026
0     2749
Name: VCL16, dtype: int64
```

In [49]:

```
columns_to_check = df.columns[54:70]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
        VCL1   VCL2   VCL3   VCL4   VCL5   VCL6   VCL7   VCL8   VCL9  VCL10
\
0      False  False  False  False  False  False  False  False  False  False
1      False  False  False  False  False  False  False  False  False  False
2      False  False  False  False  False  False  False  False  False  False
3      False  False  False  False  False  False  False  False  False  False
4      False  False  False  False  False  False  False  False  False  False
...      ...    ...    ...    ...    ...    ...    ...    ...    ...    ...
39770  False  False  False  False  False  False  False  False  False  False
39771  False  False  False  False  False  False  False  False  False  False
39772  False  False  False  False  False  False  False  False  False  False
39773  False  False  False  False  False  False  False  False  False  False
39774  False  False  False  False  False  False  False  False  False  False

       VCL11  VCL12  VCL13  VCL14  VCL15  VCL16
0      False  False  False  False  False  False
1      False  False  False  False  False  False
2      False  False  False  False  False  False
3      False  False  False  False  False  False
4      False  False  False  False  False  False
...      ...    ...    ...    ...    ...    ...
39770  False  False  False  False  False  False
39771  False  False  False  False  False  False
39772  False  False  False  False  False  False
39773  False  False  False  False  False  False
39774  False  False  False  False  False  False

[39775 rows x 16 columns]
```

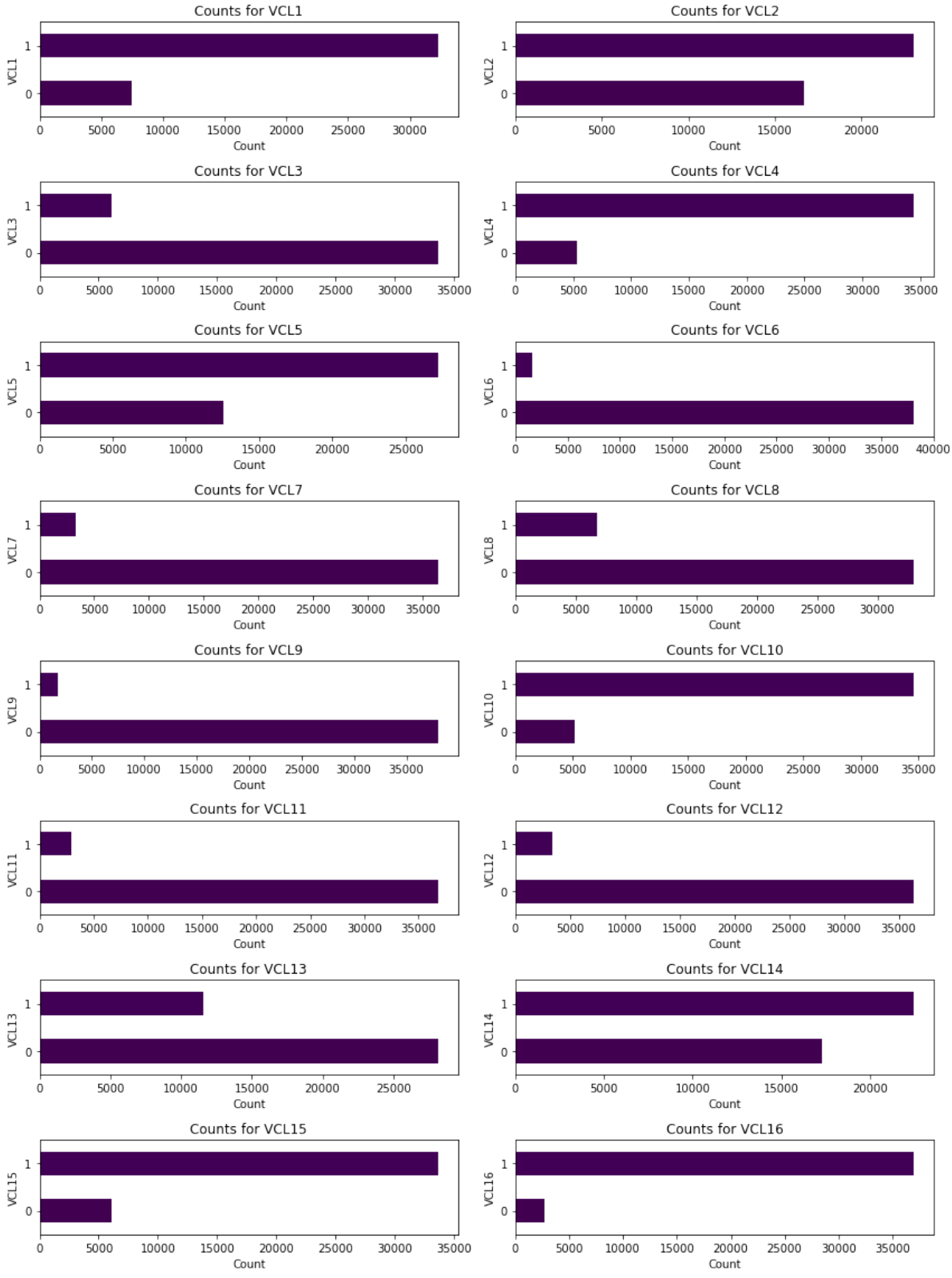


In [50]:
```
columns_to_sum = df.columns[54:70]
sum_null_values(df,columns_to_sum)
```

Out[50]:
```
{'VCL1': 0,
 'VCL2': 0,
 'VCL3': 0,
 'VCL4': 0,
 'VCL5': 0,
 'VCL6': 0,
 'VCL7': 0,
 'VCL8': 0,
 'VCL9': 0,
 'VCL10': 0,
 'VCL11': 0,
 'VCL12': 0,
 'VCL13': 0,
 'VCL14': 0,
 'VCL15': 0,
 'VCL16': 0}
```

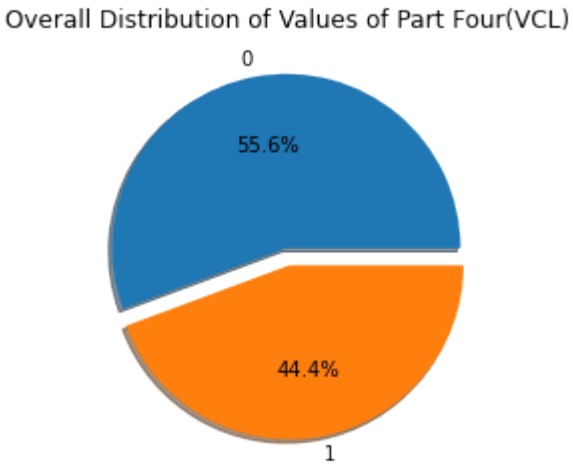
In [51]:

```
columns_to_plot = df.columns[54:70]
num_columns = 2
num_rows = math.ceil(len(columns_to_plot) / num_columns)
fig, axes = plt.subplots(nrows=num_rows, ncols=num_columns, figsize=(12, 2
for i, column in enumerate(columns_to_plot):
    row = i // num_columns
    col = i % num_columns
    ax = axes[row, col]
    counts = df[column].value_counts().sort_index()
    colors = plt.cm.viridis.colors[:len(counts)]
    counts.plot(kind='barh', ax=ax, color=colors)
    ax.set_title(f'Counts for {column}')
    ax.set_ylabel(column)
    ax.set_xlabel('Count')
for i in range(len(columns_to_plot), num_rows * num_columns):
    fig.delaxes(axes.flatten()[i])
plt.tight_layout()
plt.show()
```


Counts for VCL1
VCL1
1
0
0 5000 10000 15000 20000 25000 30000
Count
Counts for VCL2
VCL2
1
0
0 5000 10000 15000 20000
Count
Counts for VCL3
VCL3
1
0
0 5000 10000 15000 20000 25000 30000 35000
Count
Counts for VCL4
VCL4
1
0
0 5000 10000 15000 20000 25000 30000 35000
Count
Counts for VCL5
VCL5
1
0
0 5000 10000 15000 20000 25000
Count
Counts for VCL6
VCL6
1
0
0 5000 10000 15000 20000 25000 30000 35000 40000
Count
Counts for VCL7
VCL7
1
0
0 5000 10000 15000 20000 25000 30000 35000
Count
Counts for VCL8
VCL8
1
0
0 5000 10000 15000 20000 25000 30000
Count
Counts for VCL9
VCL9
1
0
0 5000 10000 15000 20000 25000 30000 35000
Count
Counts for VCL10
VCL10
1
0
0 5000 10000 15000 20000 25000 30000 35000
Count
Counts for VCL11
VCL11
1
0
0 5000 10000 15000 20000 25000 30000 35000
Count
Counts for VCL12
VCL12
1
0
0 5000 10000 15000 20000 25000 30000 35000
Count
Counts for VCL13
VCL13
1
0
0 5000 10000 15000 20000 25000
Count
Counts for VCL14
VCL14
1
0
0 5000 10000 15000 20000
Count
Counts for VCL15
VCL15
1
0
0 5000 10000 15000 20000 25000 30000 35000
Count
Counts for VCL16
VCL16
1
0
0 5000 10000 15000 20000 25000 30000 35000
Count

In [52]:

```
columns_to_plot = df.columns[54:70]
unique_values = [0, 1]
overall_value_counts = df[columns_to_plot].stack().value_counts()
total_count = overall_value_counts.sum()
overall_percentages = [overall_value_counts.get(val, 0) / total_count * 10
explode = [0.05] * len(unique_values)
plt.pie(overall_percentages, labels=unique_values, explode=explode, autopc
plt.title('Overall Distribution of Values of Part Four(VCL)')
plt.show()
```

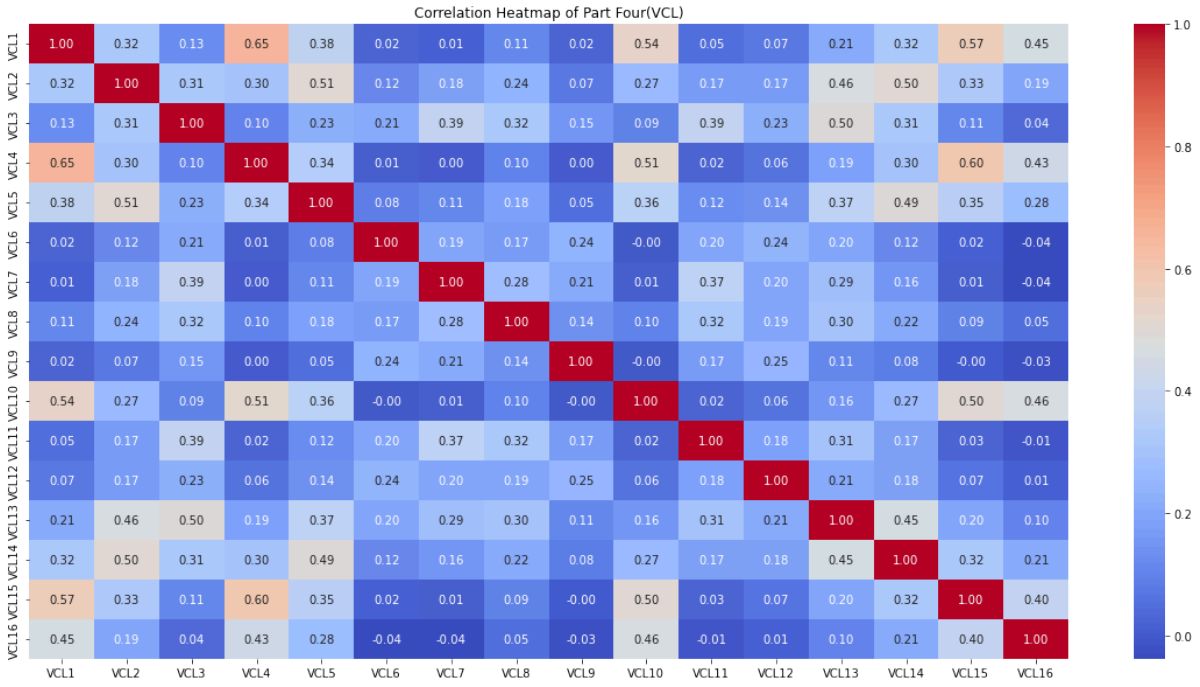


In [53]:

```
selected_columns = df.iloc[:, 54:70]
```

In [54]:

```
plt.figure(figsize=(20, 10))
sns.heatmap(selected_columns.corr(), annot=True, cmap='coolwarm', fmt=".2f
plt.title('Correlation Heatmap of Part Four(VCL)')
plt.show()
```



Part Five (General Info) :

in Education Column

In [55]:
```
1 df.columns.get_loc('education')
```

Out[55]:
```
70
```

In [56]:
```
1 df['education'].unique()
```

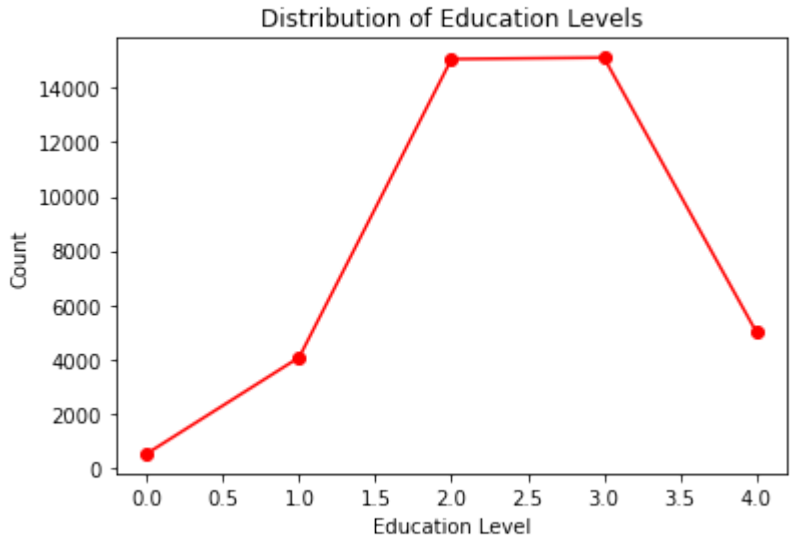
Out[56]:
```
array([2, 1, 3, 4, 0], dtype=int64)
```

In [57]:
```
1 df['education'].value_counts()
```

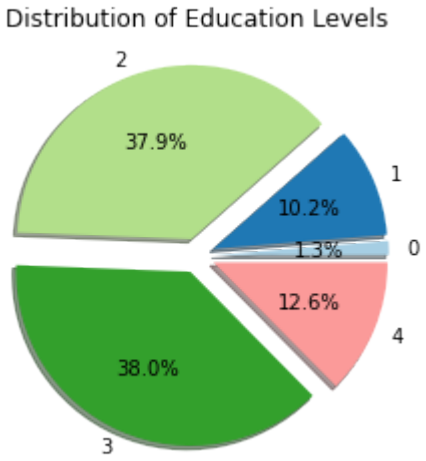
Out[57]:
```
3    15120
2    15066
4     5008
1     4066
0      515
Name: education, dtype: int64
```

In [58]:
```
1 value_counts = df['education'].value_counts().sort_index()
```

In [59]:
```
1 plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
2 plt.xlabel('Education Level')
3 plt.ylabel('Count')
4 plt.title('Distribution of Education Levels')
5 plt.show()
```



In [60]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Education Levels')
plt.show()
```



In [61]:
```
replace_zeros_with_max_frequency_inplace(df, range(70, 71))
```

In [62]:
```
df['education'].unique()
```

Out[62]:
```
array([2, 1, 3, 4], dtype=int64)
```

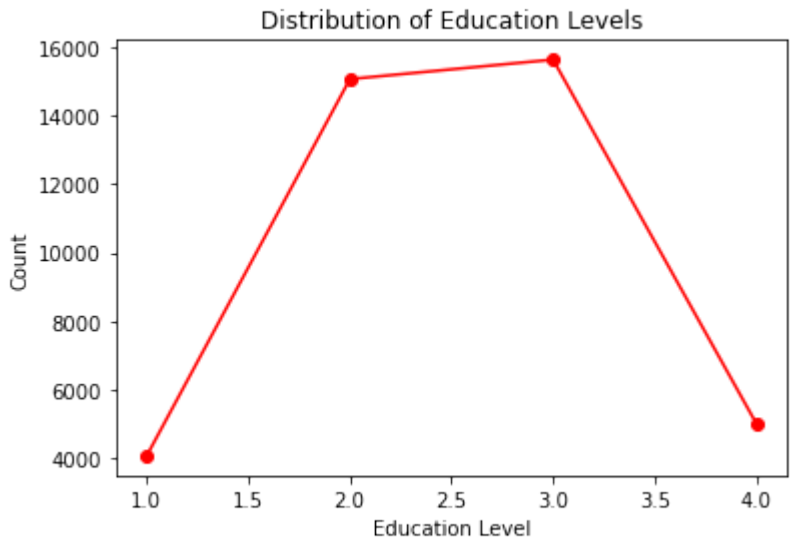
In [63]:
```
df['education'].value_counts()
```

Out[63]:
```
3    15635
2    15066
4     5008
1     4066
Name: education, dtype: int64
```

In [64]:
```
value_counts = df['education'].value_counts().sort_index()
```

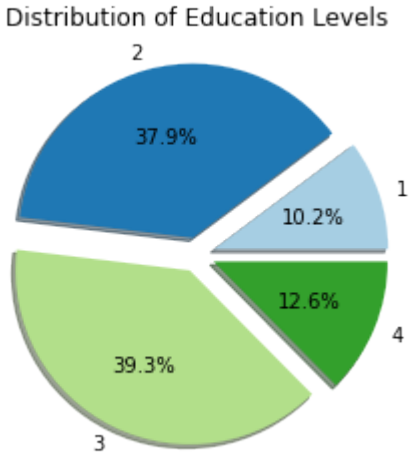
In [65]:

```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Education Level')
plt.ylabel('Count')
plt.title('Distribution of Education Levels')
plt.show()
```



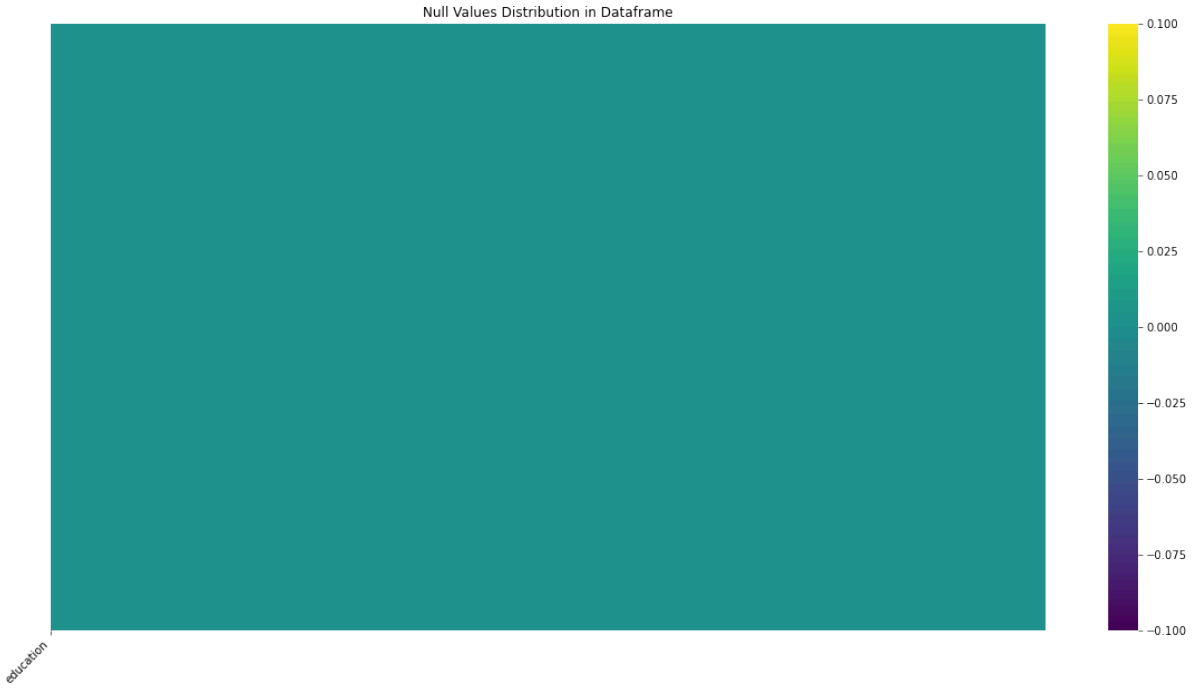
In [66]:

```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Education Levels')
plt.show()
```



In [67]:
```
columns_to_check = df.columns[70:71]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       education
0          False
1          False
2          False
3          False
4          False
...          ...
39770      False
39771      False
39772      False
39773      False
39774      False

[39775 rows x 1 columns]
```

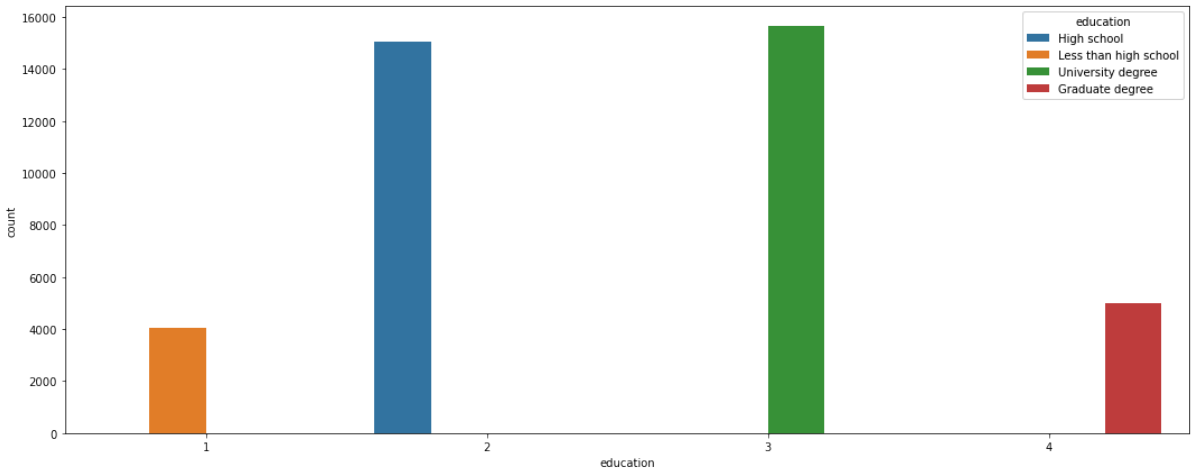


In [68]:
```
def makeEducationGroup(value):
    if value == 1:
        return 'Less than high school'
    if value == 2:
        return 'High school'
    if value == 3:
        return 'University degree'
    if value == 4:
        return 'Graduate degree'
```

In [69]:
```
education_Groups = df['education'].apply(makeEducationGroup)
```

In [70]:
```
plt.figure(figsize=(18, 7))
sns.countplot(x=df['education'], hue=education_Groups)
```

Out[70]: <AxesSubplot:xlabel='education', ylabel='count'>



in Urban Column

In [71]:
```
df.columns.get_loc('urban')
```

Out[71]: 71

In [72]:
```
df['urban'].unique()
```

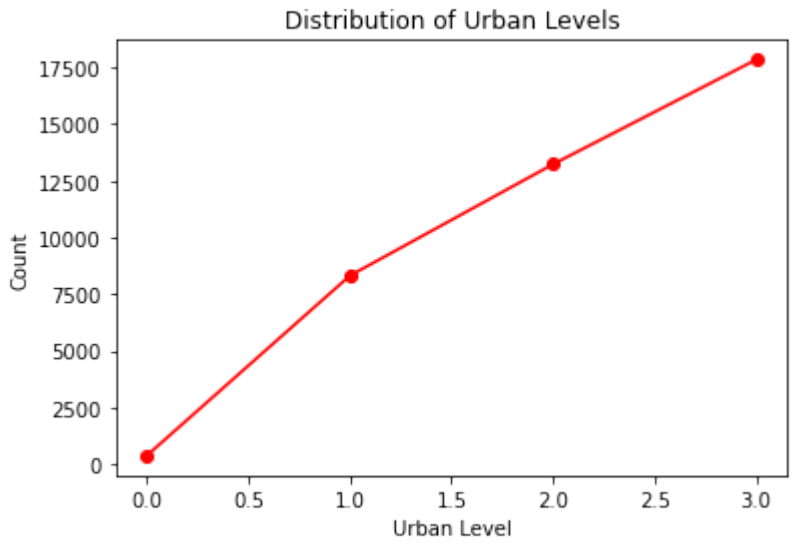
Out[72]: array([3, 2, 1, 0], dtype=int64)

In [73]:
```
df['urban'].value_counts()
```

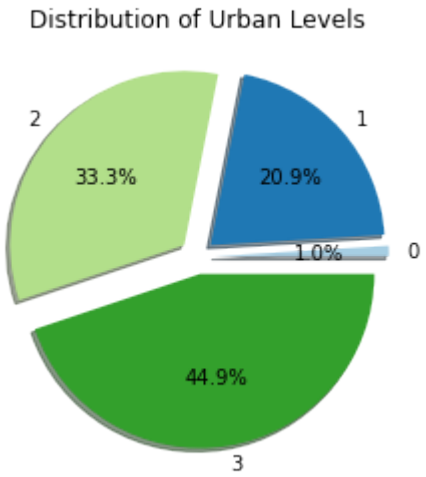
Out[73]:
```
3    17843
2    13232
1     8318
0      382
Name: urban, dtype: int64
```

In [74]:
```
value_counts = df['urban'].value_counts().sort_index()
```

In [75]:
```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Urban Level')
plt.ylabel('Count')
plt.title('Distribution of Urban Levels')
plt.show()
```



In [76]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Urban Levels')
plt.show()
```



In [77]:
```
replace_zeros_with_max_frequency_inplace(df, range(71, 72))
```

In [78]:
```
df['urban'].unique()
```

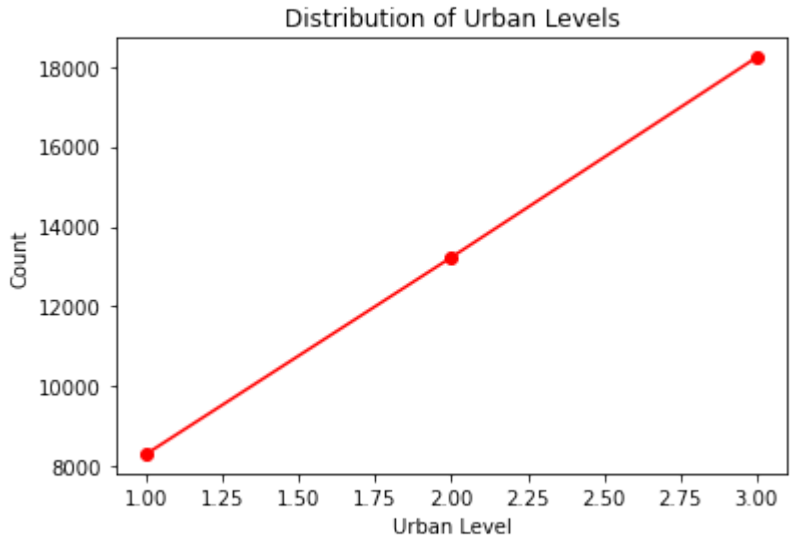
Out[78]:
```
array([3, 2, 1], dtype=int64)
```

In [79]:
```
df['urban'].value_counts()
```

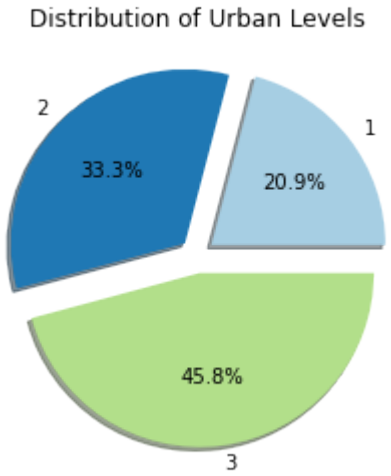
Out[79]:
```
3    18225
2    13232
1     8318
Name: urban, dtype: int64
```

In [80]:
```
value_counts = df['urban'].value_counts().sort_index()
```

In [81]:
```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Urban Level')
plt.ylabel('Count')
plt.title('Distribution of Urban Levels')
plt.show()
```

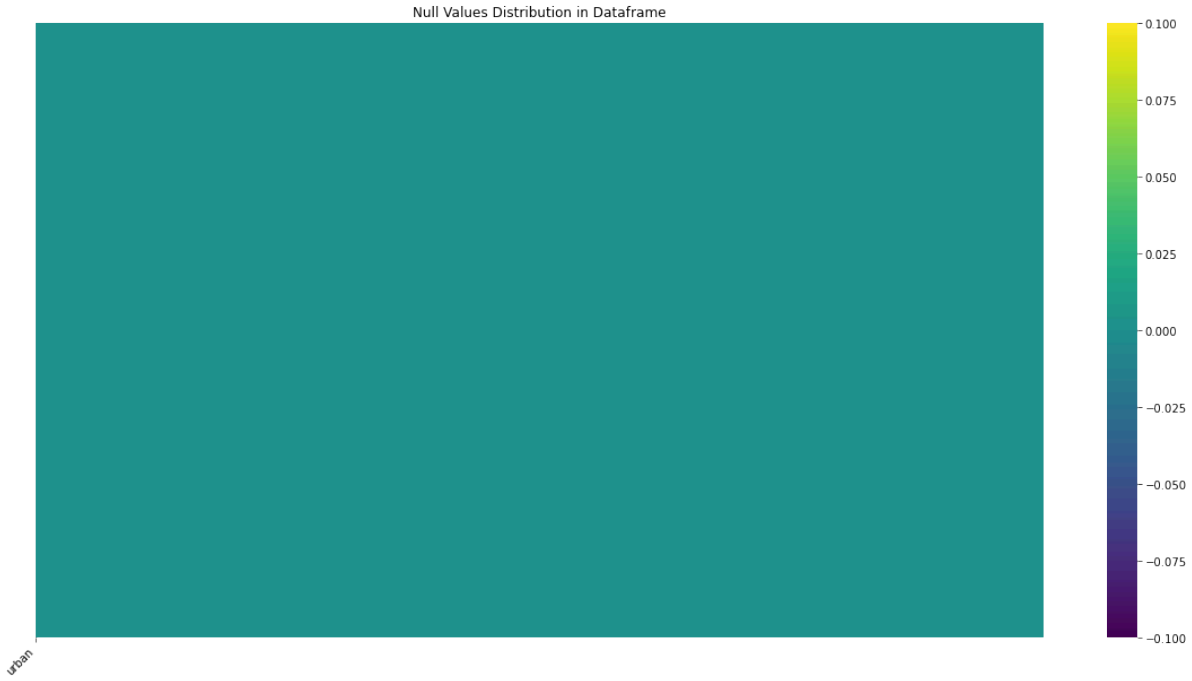


In [82]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Urban Levels')
plt.show()
```



In [83]:
```
columns_to_check = df.columns[71:72]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       urban
0      False
1      False
2      False
3      False
4      False
...      ...
39770  False
39771  False
39772  False
39773  False
39774  False

[39775 rows x 1 columns]
```

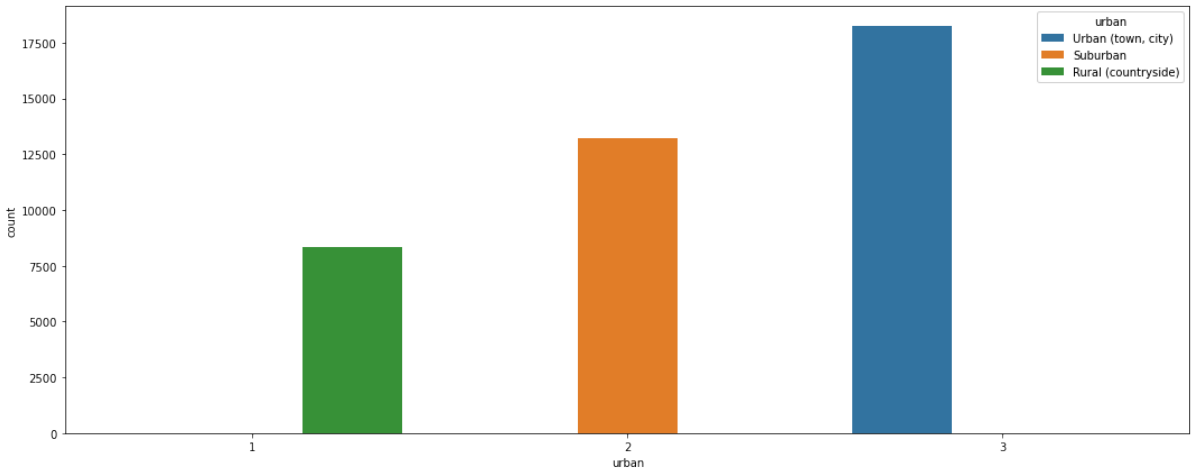


In [84]:
```
def makeUrbanGroup(value):
    if value == 1:
        return 'Rural (countryside)'
    if value == 2:
        return 'Suburban'
    if value == 3:
        return 'Urban (town, city)'
```

In [85]:
```
Urban = df['urban'].apply(makeUrbanGroup)
```

In [86]:
```
1 plt.figure(figsize=(18, 7))
2 sns.countplot(x=df['urban'], hue=Urban)
```

Out[86]: <AxesSubplot:xlabel='urban', ylabel='count'>



in Gender Column

In [87]:
```
1 df.columns.get_loc('gender')
```

Out[87]: 72

In [88]:
```
1 df['gender'].unique()
```

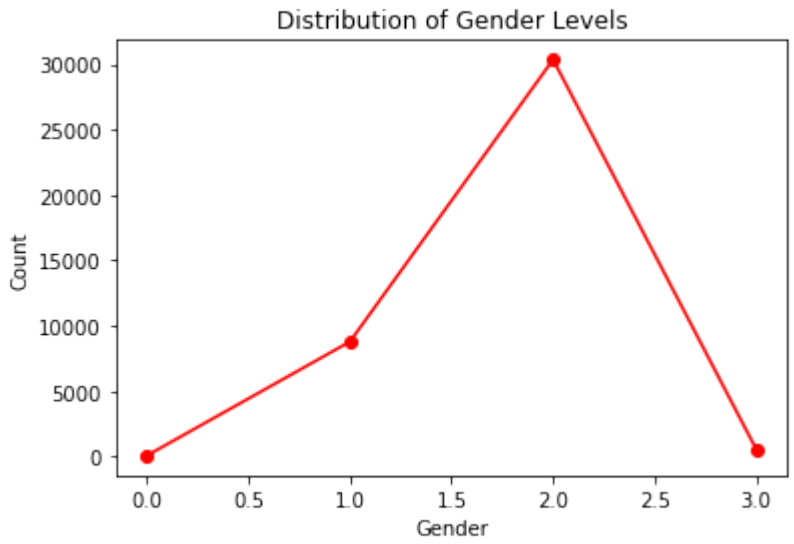
Out[88]: array([2, 1, 3, 0], dtype=int64)

In [89]:
```
1 df['gender'].value_counts()
```

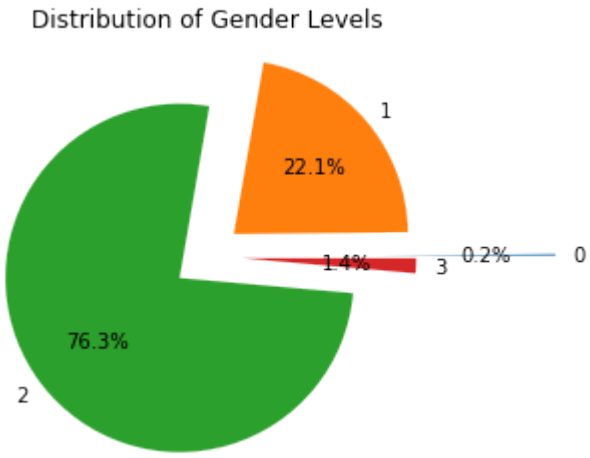
Out[89]:
```
2    30367
1     8789
3      552
0       67
Name: gender, dtype: int64
```

In [90]:
```
1 value_counts = df['gender'].value_counts().sort_index()
```

In [91]:
```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.title('Distribution of Gender Levels')
plt.show()
```



In [92]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=[1,0.2,0.2,0.2],
plt.title('Distribution of Gender Levels')
plt.show()
```



In [93]:
```
replace_zeros_with_max_frequency_inplace(df, range(72, 73))
```

In [94]:
```
df['gender'].unique()
```

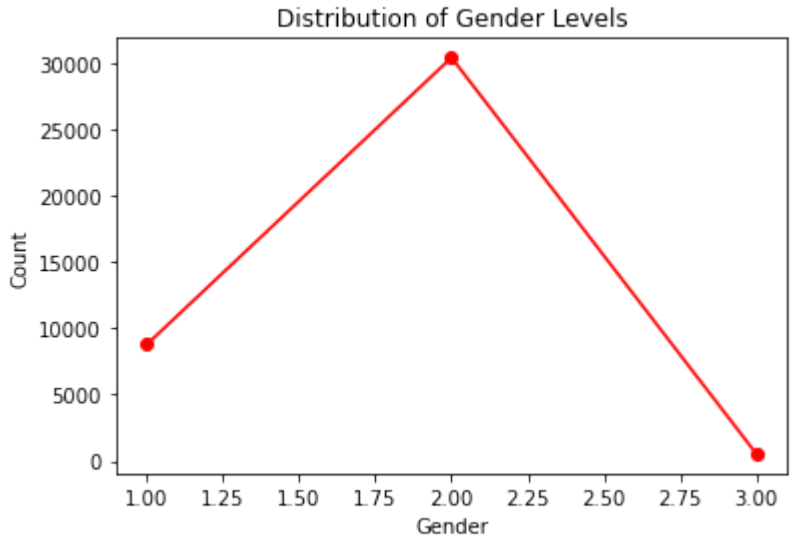
Out[94]:
```
array([2, 1, 3], dtype=int64)
```

In [95]:
```
df['gender'].value_counts()
```

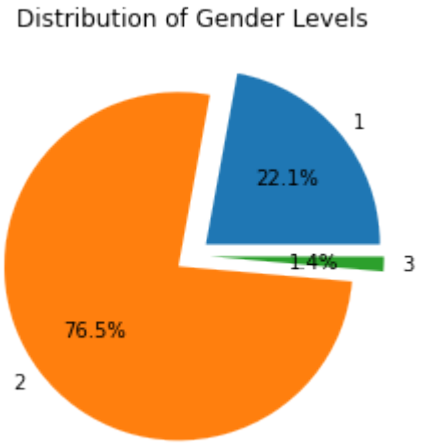
Out[95]:
```
2    30434
1     8789
3      552
Name: gender, dtype: int64
```

In [96]:
```
value_counts = df['gender'].value_counts().sort_index()
```

In [97]:
```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.title('Distribution of Gender Levels')
plt.show()
```

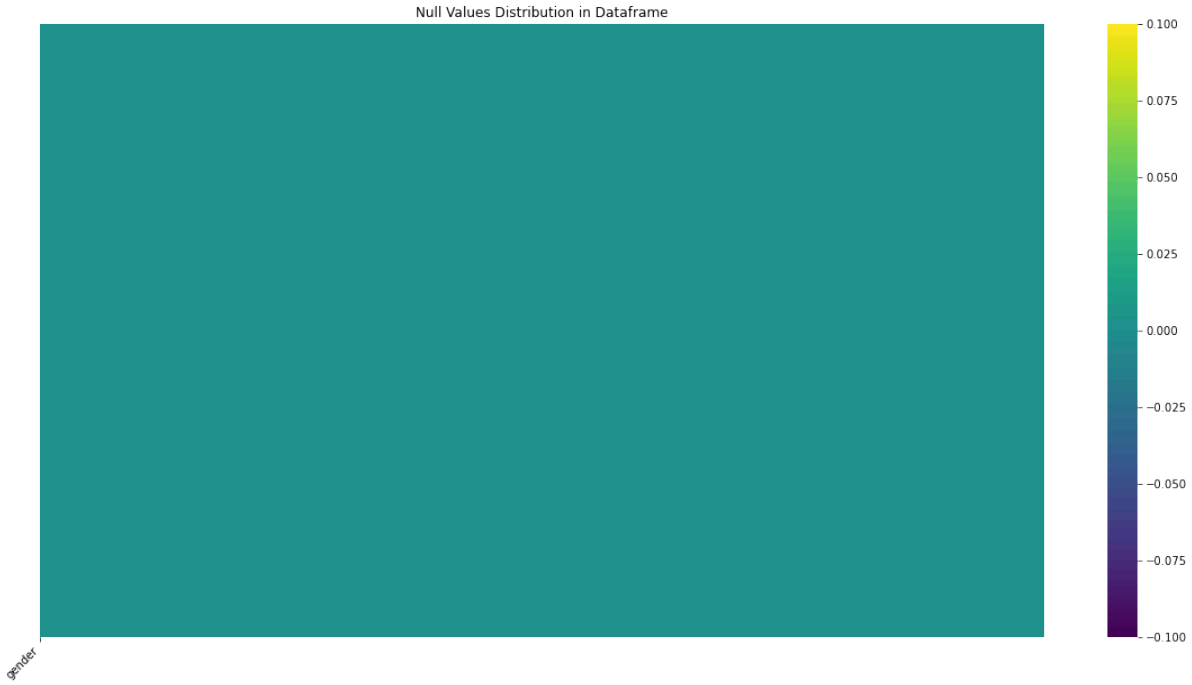


In [98]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Gender Levels')
plt.show()
```



In [99]:
```
columns_to_check = df.columns[72:73]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       gender
0       False
1       False
2       False
3       False
4       False
...       ...
39770   False
39771   False
39772   False
39773   False
39774   False

[39775 rows x 1 columns]
```

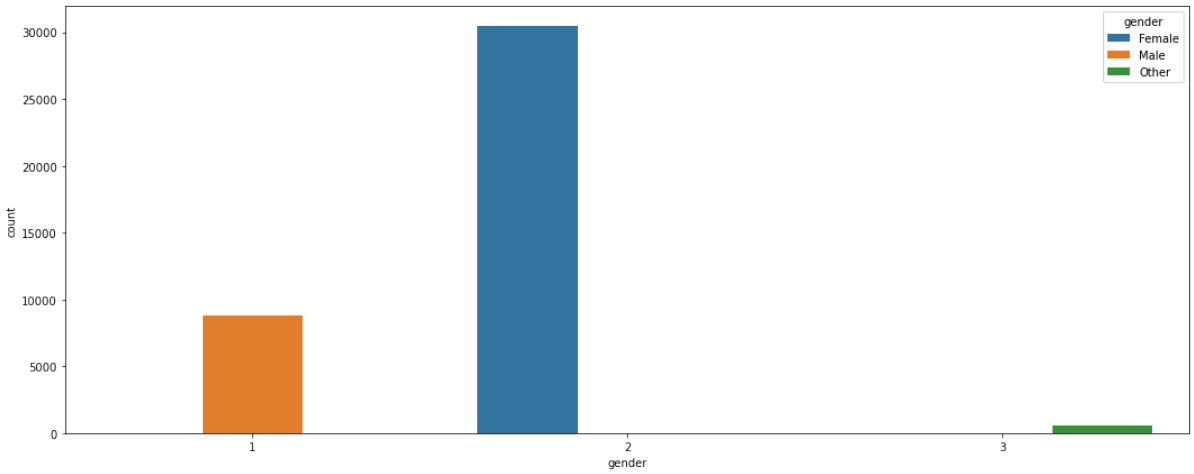


In [100]:
```
def makeGenderGroup(value):
    if value == 1:
        return 'Male'
    if value == 2:
        return 'Female'
    if value == 3:
        return 'Other'
```

In [101]:
```
gender = df['gender'].apply(makeGenderGroup)
```

In [102]:
```
1 plt.figure(figsize=(18, 7))
2 sns.countplot(x=df['gender'], hue=gender)
```

Out[102]: <AxesSubplot:xlabel='gender', ylabel='count'>



in Engnat column

In [103]:
```
1 df.columns.get_loc('engnat')
```

Out[103]: 73

In [104]:
```
1 df['engnat'].unique()
```

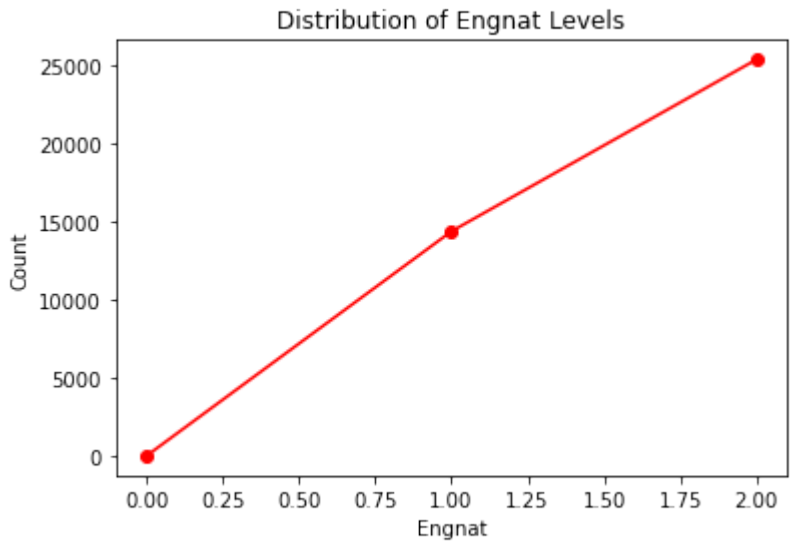
Out[104]: array([2, 1, 0], dtype=int64)

In [105]:
```
1 df['gender'].value_counts()
```

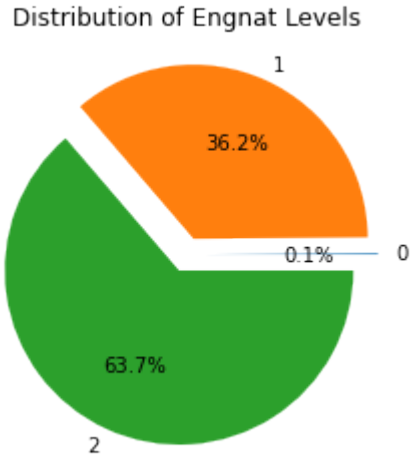
Out[105]:
```
2    30434
1     8789
3      552
Name: gender, dtype: int64
```

In [106]:
```
1 value_counts = df['engnat'].value_counts().sort_index()
```

In [107]:
```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Engnat')
plt.ylabel('Count')
plt.title('Distribution of Engnat Levels')
plt.show()
```



In [108]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Engnat Levels')
plt.show()
```



In [109]:
```
replace_zeros_with_max_frequency_inplace(df, range(73, 74))
```

In [110]:
```
df['engnat'].unique()
```

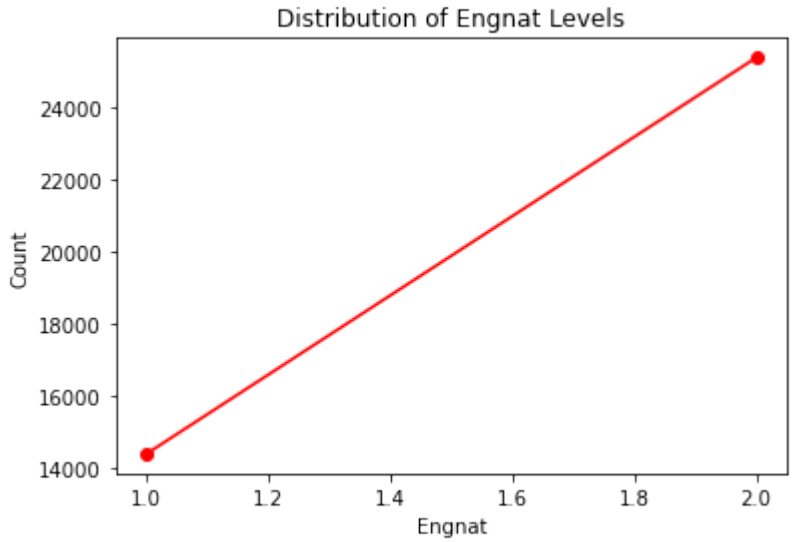
Out[110]:
```
array([2, 1], dtype=int64)
```

In [111]:
```
1 df['engnat'].value_counts()
```

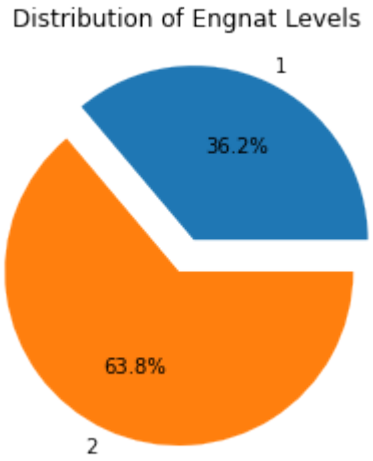
Out[111]:
```
2    25395
1    14380
Name: engnat, dtype: int64
```

In [112]:
```
1 value_counts = df['engnat'].value_counts().sort_index()
```

In [113]:
```
1 plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
2 plt.xlabel('Engnat')
3 plt.ylabel('Count')
4 plt.title('Distribution of Engnat Levels')
5 plt.show()
```

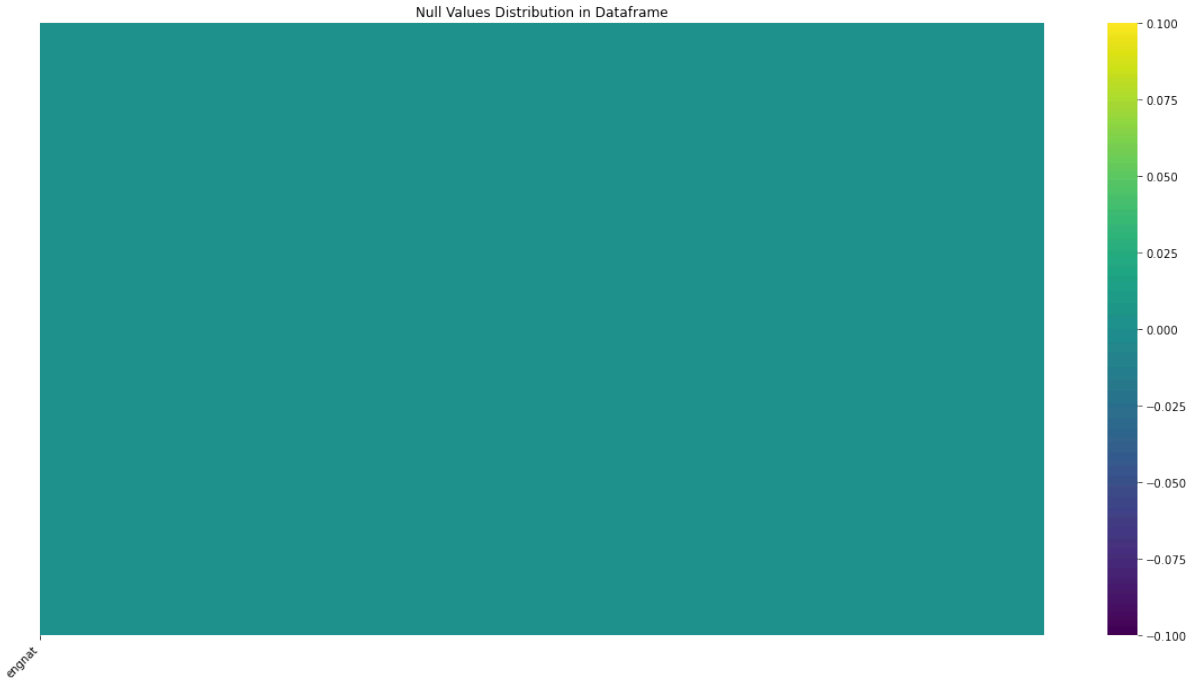


In [114]:
```
1 explode_values = [0.1] * len(value_counts)
2 plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
3 plt.title('Distribution of Engnat Levels')
4 plt.show()
```



In [115]:
```
columns_to_check = df.columns[73:74]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       engnat
0       False
1       False
2       False
3       False
4       False
...       ...
39770   False
39771   False
39772   False
39773   False
39774   False

[39775 rows x 1 columns]
```

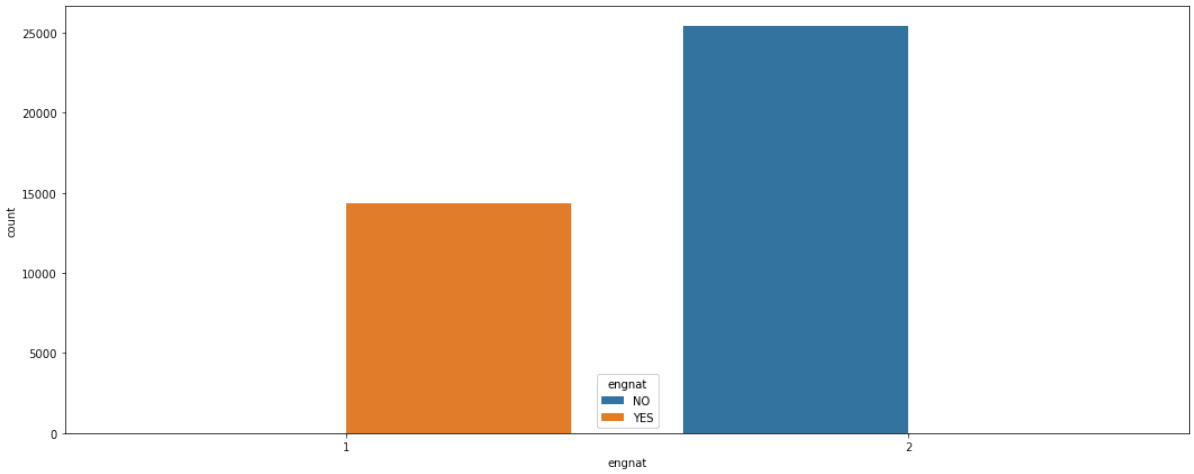


In [116]:
```
def makeEngnatGroup(value):
    if value == 1:
        return 'YES'
    if value == 2:
        return 'NO'
```

In [117]:
```
engnat = df['engnat'].apply(makeEngnatGroup)
```

In [118]:
```
1 plt.figure(figsize=(18, 7))
2 sns.countplot(x=df['engnat'], hue=engnat)
```

Out[118]: <AxesSubplot:xlabel='engnat', ylabel='count'>



in Age column

In [119]:
```
1 df.columns.get_loc('age')
```

Out[119]: 74

In [120]:
```
1 df['age'].unique()
```

Out[120]:
```
array([  16,   17,   13,   19,   20,   29,   18,   15,   31,   34,   22,
         42,   21,   23,   26,   43,   35,   25,   24,   61,   40,   27,
         28,   60,   14,   37,   46,   57,   41,   55,   36,   30,   32,
         56,   71,   67,   44,   38,   49,   45,   47,   33,   54,   53,
         50,   48,   58,   68,   39,   51,   62,   59,   52,   77,   85,
         63,   69,   65,   75,   72,   70,   73,   64,   66,   79,   80,
         78,  223, 1996,   89,  117,   82,   74, 1998,   76,  115, 1993,
       1991,   99], dtype=int64)
```

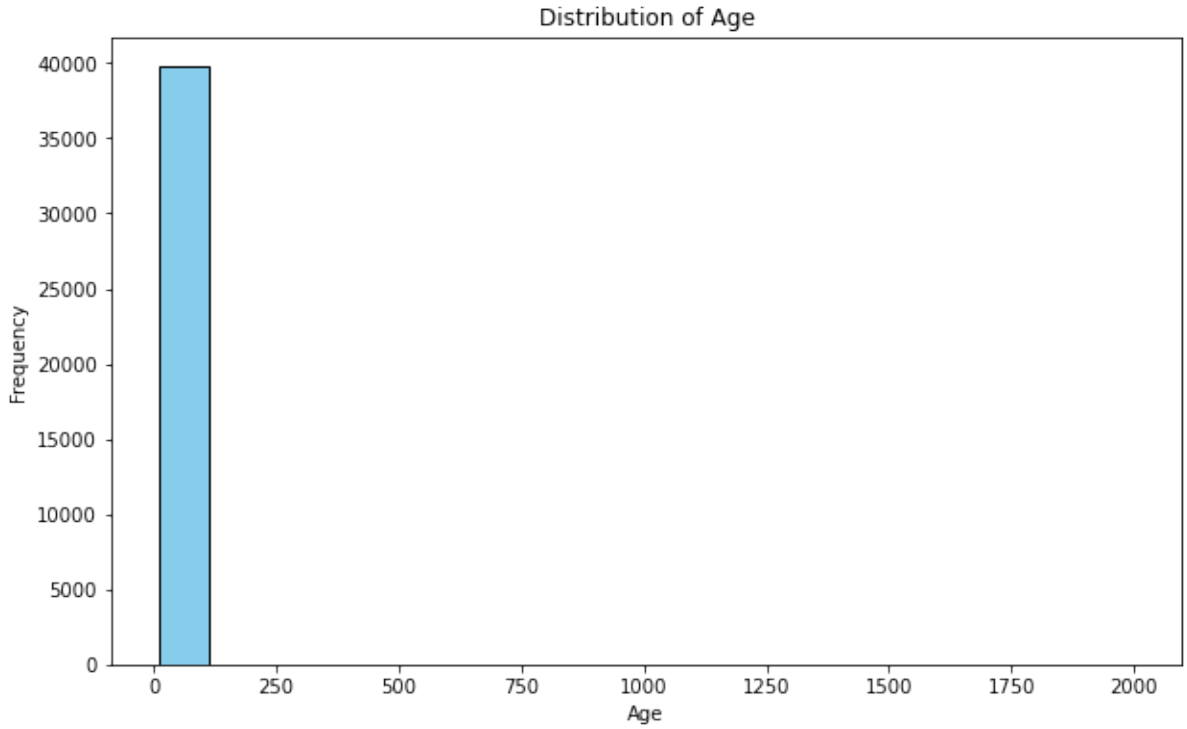
In [121]:
```
1 df['age'].describe()
```

Out[121]:
```
count   39775.00
mean       23.61
std        21.58
min        13.00
25%        18.00
50%        21.00
75%        25.00
max      1998.00
Name: age, dtype: float64
```

In [122]:
```
df['age'].value_counts()
```

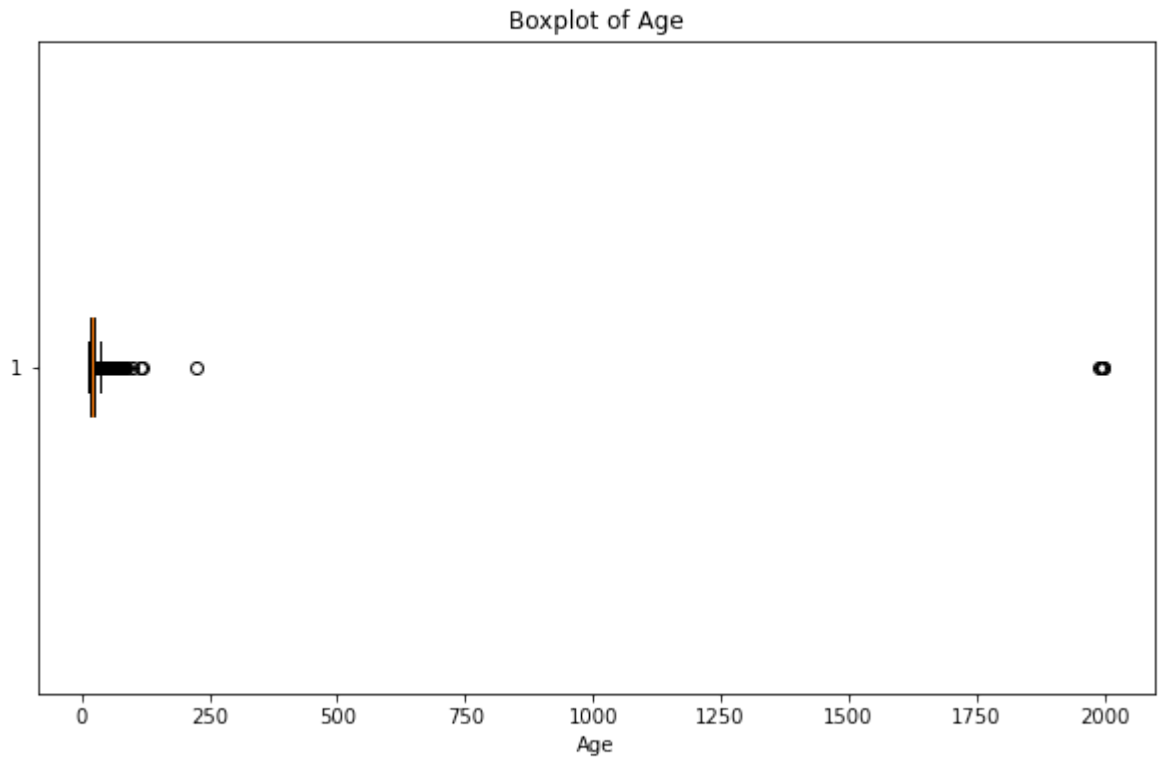
Out[122]:
```
20      3789
21      3535
19      3510
18      3046
22      3009
        ...
89         1
1996       1
223        1
78         1
99         1
Name: age, Length: 79, dtype: int64
```

In [123]:
```
plt.figure(figsize=(10, 6))
plt.hist(df['age'], bins=20, color='skyblue', edgecolor='black')
plt.title('Distribution of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



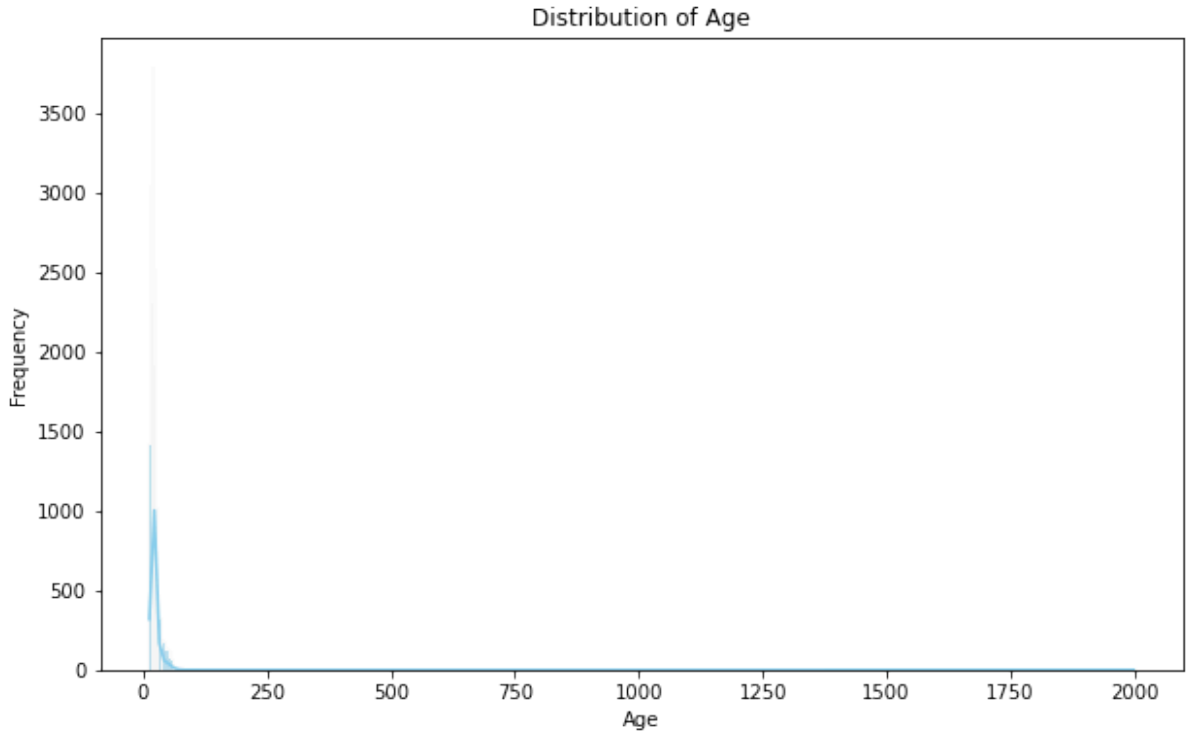
In [124]:

```
plt.figure(figsize=(10, 6))
plt.boxplot(df['age'], vert=False, patch_artist=True)
plt.title('Boxplot of Age')
plt.xlabel('Age')
plt.show()
```

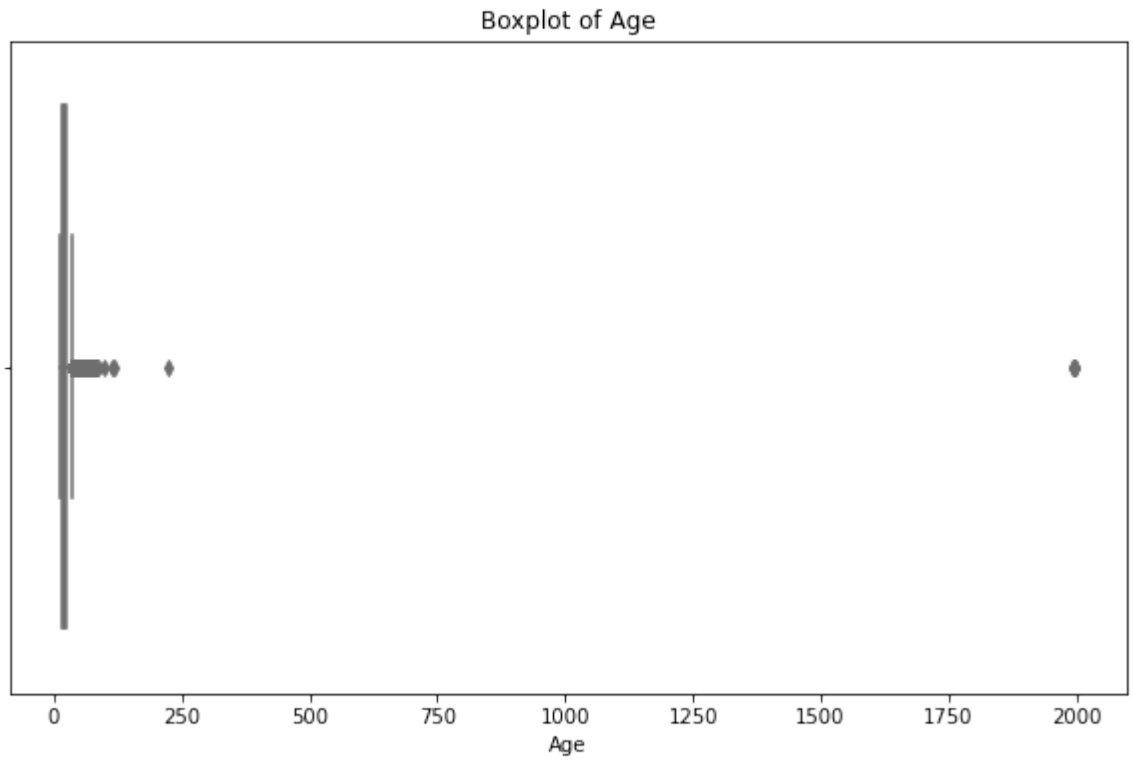


In [125]:

```
plt.figure(figsize=(10, 6))
sns.histplot(df['age'], kde=True, color='skyblue')
plt.title('Distribution of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



In [126]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x=df['age'], color='lightcoral')
plt.title('Boxplot of Age')
plt.xlabel('Age')
plt.show()
```



In [127]:
```
age = df[(df['age'] >= 13) & (df['age'] <= 100)]
```

In [128]:
```
scaler = MinMaxScaler()
df['scaled_age'] = scaler.fit_transform(df[['age']])
```

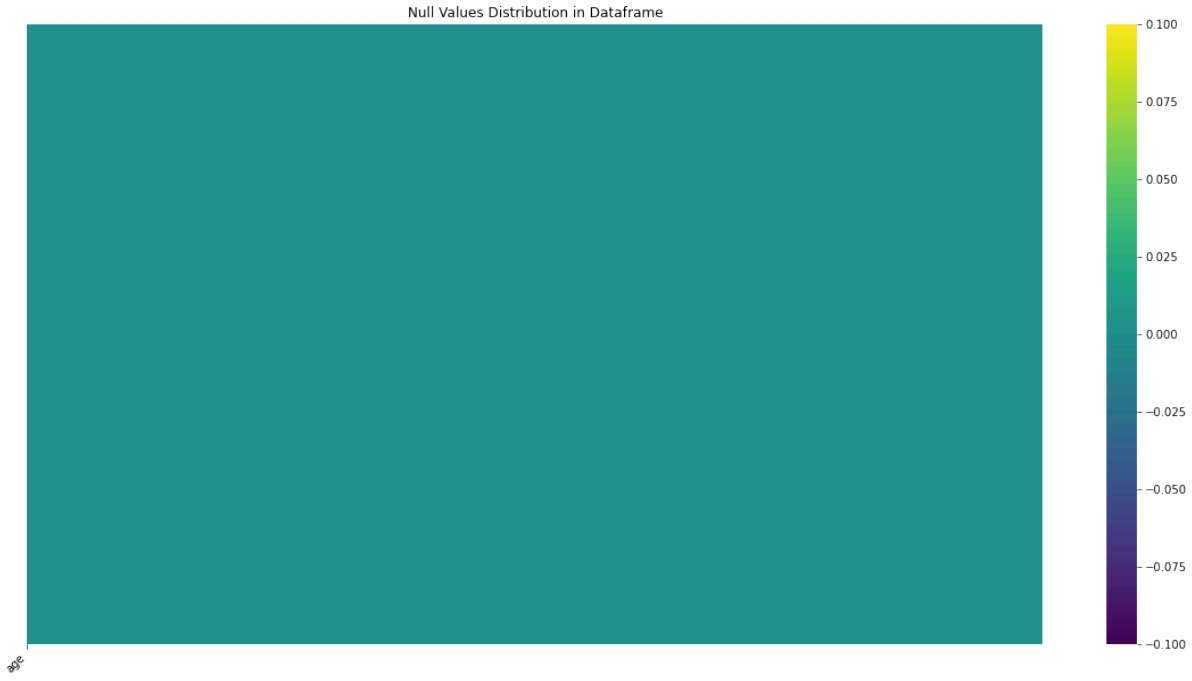
In [129]:
```
df['age']
```

Out[129]:
```
0        16
1        16
2        17
3        13
4        19
        ..
39770    16
39771    21
39772    48
39773    20
39774    26
Name: age, Length: 39775, dtype: int64
```

In [130]:

```
columns_to_check = df.columns[74:75]
plot_null_values(df, columns_to_check)
```

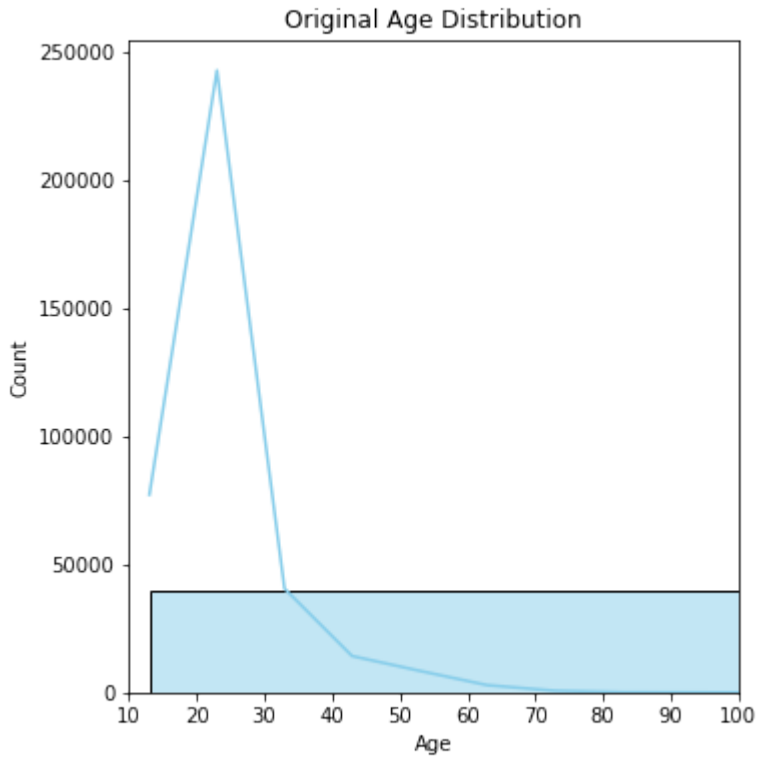
```
Null values in the specified columns:
         age
0      False
1      False
2      False
3      False
4      False
...      ...
39770  False
39771  False
39772  False
39773  False
39774  False

[39775 rows x 1 columns]
```



In [131]:

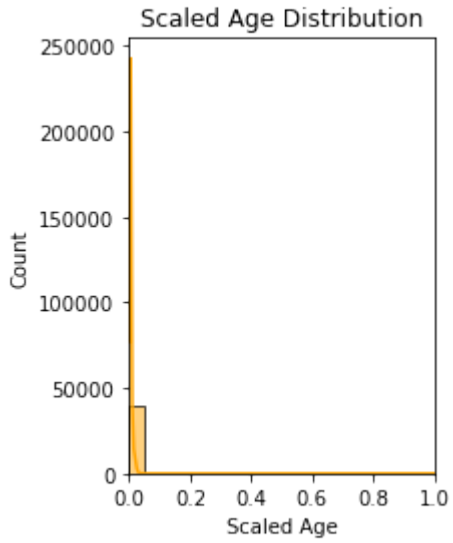
```
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.histplot(df['age'], bins=20, kde=True, color='skyblue')
plt.title('Original Age Distribution')
plt.xlabel('Age')
plt.xlim(10, 100)
```

Out[131]: (10.0, 100.0)

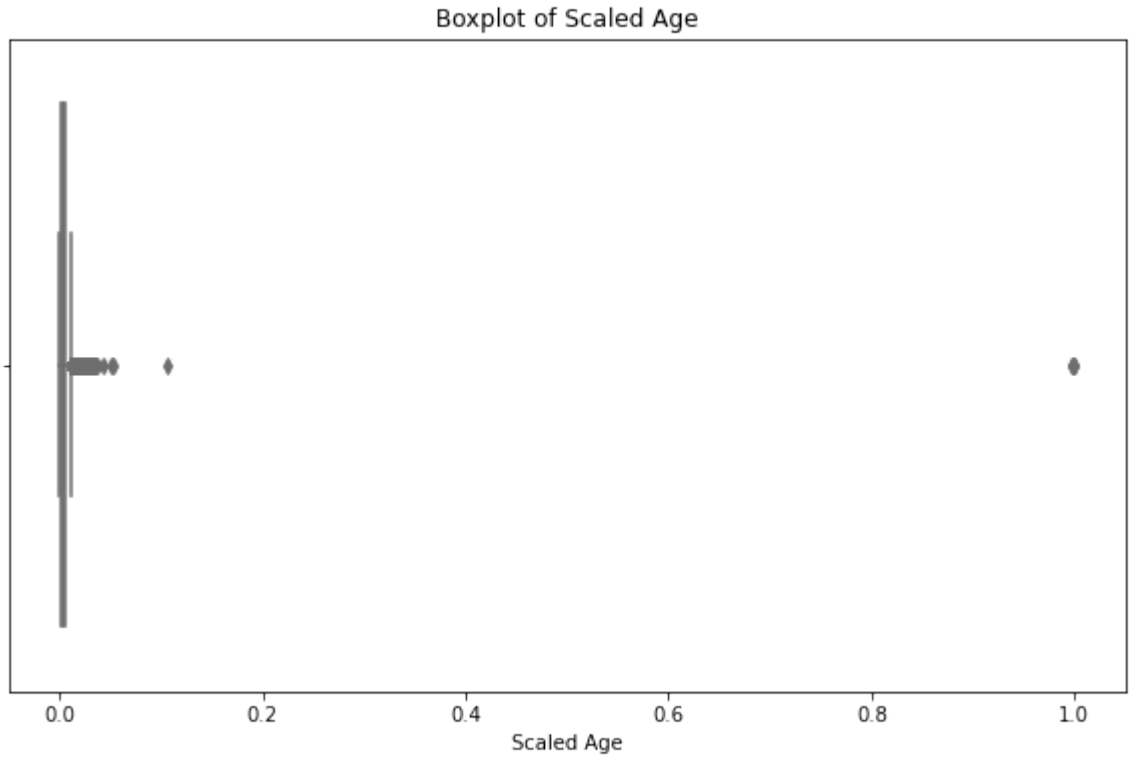


In [132]:
```
plt.subplot(1, 2, 2)
sns.histplot(df['scaled_age'], bins=20, kde=True, color='orange')
plt.title('Scaled Age Distribution')
plt.xlabel('Scaled Age')
plt.xlim(0, 1)
```

Out[132]: (0.0, 1.0)



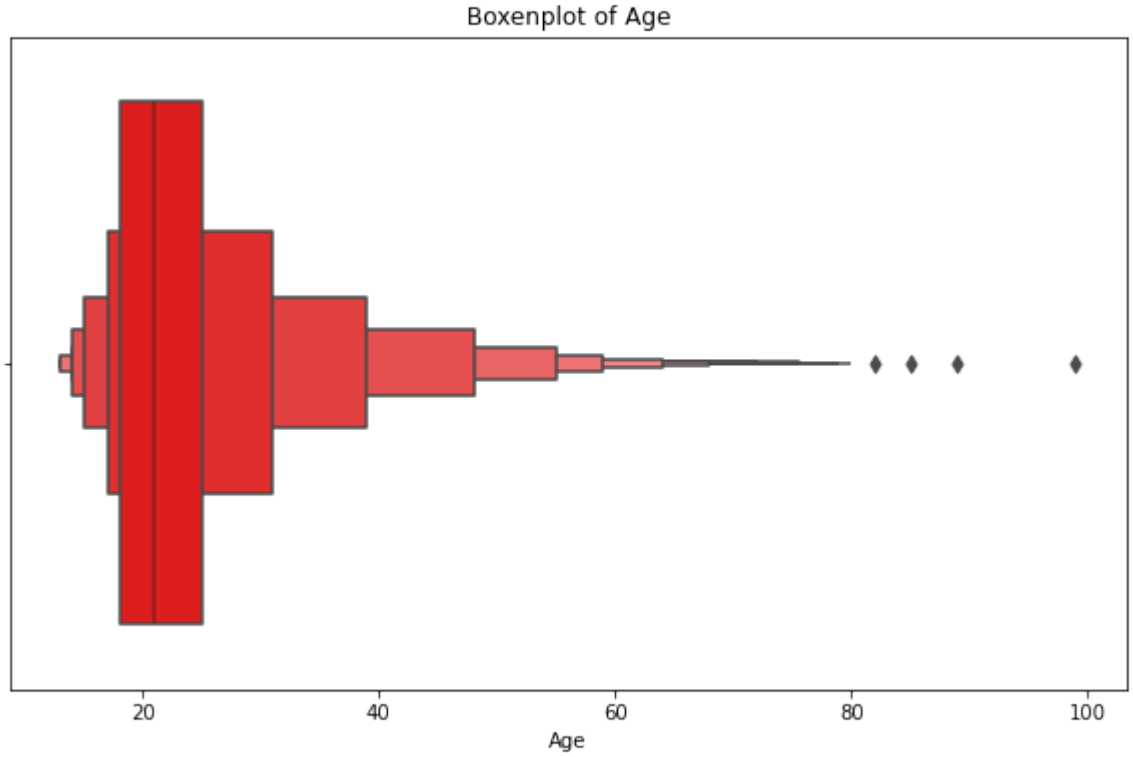
In [133]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x=df['scaled_age'], color='lightcoral')
plt.title('Boxplot of Scaled Age')
plt.xlabel('Scaled Age')
plt.show()
```



In [134]:
```
age_indexes = df[df['age'] > 100]['age'].index
display(age_indexes)
print(f'DataFrame size before: {df.shape[0]}')
df.drop(age_indexes, axis=0, inplace=True)
print(f'DataFrame size after: {df.shape[0]}')
```

```
Int64Index([5340, 10231, 14236, 21383, 24898, 30027, 33730], dtype='int64')

DataFrame size before: 39775
DataFrame size after: 39768
```

In [135]:
```
plt.figure(figsize=(10, 6))
sns.boxenplot(x=df['age'], color='red')
plt.title('Boxenplot of Age')
plt.xlabel('Age')
plt.show()
```



In [136]:
```
1 df.columns
```

Out[136]:
```
Index(['Q1A', 'Q2A', 'Q3A', 'Q4A', 'Q5A', 'Q6A', 'Q7A', 'Q8A', 'Q9A', 'Q10A',
       'Q11A', 'Q12A', 'Q13A', 'Q14A', 'Q15A', 'Q16A', 'Q17A', 'Q18A', 'Q19
A',
       'Q20A', 'Q21A', 'Q22A', 'Q23A', 'Q24A', 'Q25A', 'Q26A', 'Q27A', 'Q28
A',
       'Q29A', 'Q30A', 'Q31A', 'Q32A', 'Q33A', 'Q34A', 'Q35A', 'Q36A', 'Q37
A',
       'Q38A', 'Q39A', 'Q40A', 'Q41A', 'Q42A', 'country', 'source', 'TIPI1',
       'TIPI2', 'TIPI3', 'TIPI4', 'TIPI5', 'TIPI6', 'TIPI7', 'TIPI8', 'TIPI
9',
       'TIPI10', 'VCL1', 'VCL2', 'VCL3', 'VCL4', 'VCL5', 'VCL6', 'VCL7',
       'VCL8', 'VCL9', 'VCL10', 'VCL11', 'VCL12', 'VCL13', 'VCL14', 'VCL15',
       'VCL16', 'education', 'urban', 'gender', 'engnat', 'age', 'screensiz
e',
       'uniquenetworklocation', 'hand', 'religion', 'orientation', 'race',
       'voted', 'married', 'familysize', 'major', 'scaled_age'],
      dtype='object')
```

In [137]:
```
1 df = df.drop('scaled_age', axis=1)
```

In [138]:
```
1 df.columns
```

Out[138]:
```
Index(['Q1A', 'Q2A', 'Q3A', 'Q4A', 'Q5A', 'Q6A', 'Q7A', 'Q8A', 'Q9A', 'Q10A',
       'Q11A', 'Q12A', 'Q13A', 'Q14A', 'Q15A', 'Q16A', 'Q17A', 'Q18A', 'Q19
A',
       'Q20A', 'Q21A', 'Q22A', 'Q23A', 'Q24A', 'Q25A', 'Q26A', 'Q27A', 'Q28
A',
       'Q29A', 'Q30A', 'Q31A', 'Q32A', 'Q33A', 'Q34A', 'Q35A', 'Q36A', 'Q37
A',
       'Q38A', 'Q39A', 'Q40A', 'Q41A', 'Q42A', 'country', 'source', 'TIPI1',
       'TIPI2', 'TIPI3', 'TIPI4', 'TIPI5', 'TIPI6', 'TIPI7', 'TIPI8', 'TIPI
9',
       'TIPI10', 'VCL1', 'VCL2', 'VCL3', 'VCL4', 'VCL5', 'VCL6', 'VCL7',
       'VCL8', 'VCL9', 'VCL10', 'VCL11', 'VCL12', 'VCL13', 'VCL14', 'VCL15',
       'VCL16', 'education', 'urban', 'gender', 'engnat', 'age', 'screensiz
e',
       'uniquenetworklocation', 'hand', 'religion', 'orientation', 'race',
       'voted', 'married', 'familysize', 'major'],
      dtype='object')
```

In [139]:
```
1 df.shape
```

Out[139]:
```
(39768, 85)
```

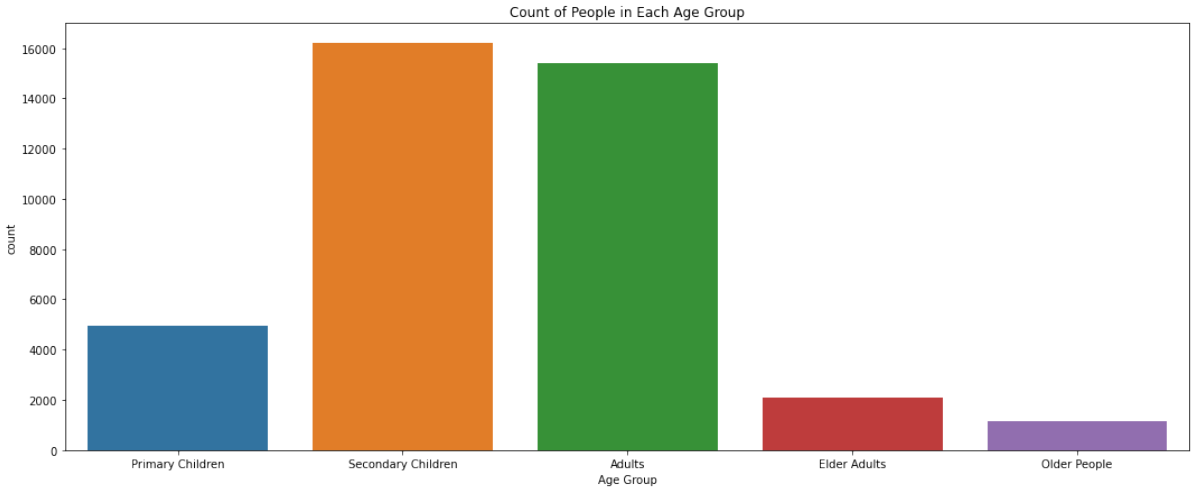
In [140]:
```
1 df['age'].unique()
```

Out[140]:
```
array([16, 17, 13, 19, 20, 29, 18, 15, 31, 34, 22, 42, 21, 23, 26, 43, 35,
       25, 24, 61, 40, 27, 28, 60, 14, 37, 46, 57, 41, 55, 36, 30, 32, 56,
       71, 67, 44, 38, 49, 45, 47, 33, 54, 53, 50, 48, 58, 68, 39, 51, 62,
       59, 52, 77, 85, 63, 69, 65, 75, 72, 70, 73, 64, 66, 79, 80, 78, 89,
       82, 74, 76, 99], dtype=int64)
```

In [141]:
```
def makeAgeGroup(value):
    if value <= 10:
        return 'Under 10'
    if  10 <= value <= 16:
        return 'Primary Children'
    if 17 <= value <= 21:
        return 'Secondary Children'
    if 21 <= value <= 35:
        return 'Adults'
    if 36 <= value <= 48:
        return 'Elder Adults'
    if value >= 49:
        return 'Older People'
```

In [142]:
```
age_group = df['age'].apply(makeAgeGroup)
```

In [143]:
```
plt.figure(figsize=(18, 7))
sns.countplot(x=age_group)
plt.title('Count of People in Each Age Group')
plt.xlabel('Age Group')
plt.show()
```



In [144]:
```
def makeAgeGroupFeature(value):
    if value <= 10:
        return 1
    if  10 <= value <= 16:
        return 2
    if 17 <= value <= 21:
        return 3
    if 21 <= value <= 35:
        return 4
    if 36 <= value <= 48:
        return 5
    if value >= 49:
        return 6
```

In [145]:
```
df['age_group'] = df['age'].apply(makeAgeGroupFeature)
df
```

Out[145]:

	Q1A	Q2A	Q3A	Q4A	Q5A	Q6A	Q7A	Q8A	Q9A	Q10A	Q11A	Q12A	Q13A	Q14A	Q
0	4	4	2	4	4	4	4	4	2	1	4	4	4	4	
1	4	1	2	3	4	4	3	4	3	2	2	2	4	4	
2	3	1	4	1	4	3	1	3	2	4	2	1	4	1	
3	2	3	2	1	3	3	4	2	3	3	2	1	1	4	
4	2	2	3	4	4	2	4	4	4	3	2	4	4	4	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
39770	2	1	3	2	3	2	1	3	1	4	2	2	4	2	
39771	3	4	3	4	3	4	4	4	3	4	4	4	4	4	
39772	2	1	2	1	1	1	1	1	2	1	1	1	2	1	
39773	3	1	2	2	3	3	3	4	3	1	3	3	4	4	
39774	2	1	2	1	4	2	1	1	1	1	3	1	3	1	

39768 rows × 86 columns

in Hand Column

In [146]:
```
df.columns.get_loc('hand')
```

Out[146]:
```
77
```

In [147]:
```
df['hand'].unique()
```

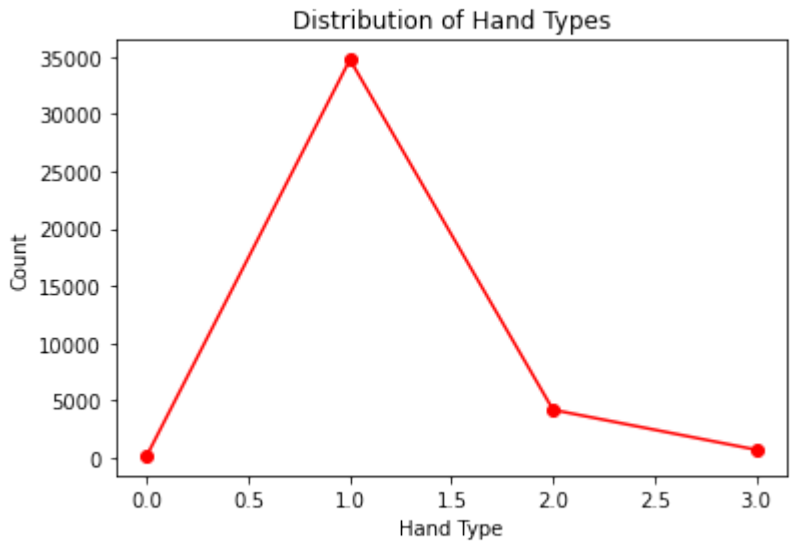
Out[147]:
```
array([1, 2, 3, 0], dtype=int64)
```

In [148]:
```
df['hand'].value_counts()
```

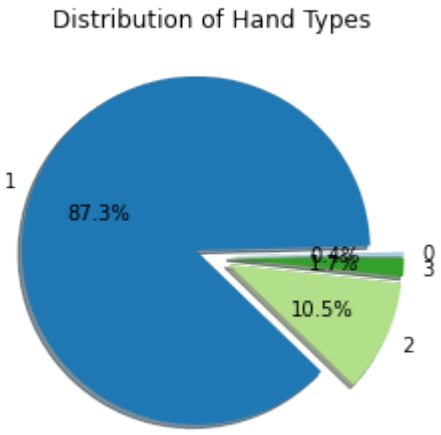
Out[148]:
```
1    34735
2     4171
3      689
0      173
Name: hand, dtype: int64
```

In [149]:
```
value_counts = df['hand'].value_counts().sort_index()
```

In [150]:
```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Hand Type')
plt.ylabel('Count')
plt.title('Distribution of Hand Types')
plt.show()
```



In [151]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Hand Types')
plt.show()
```



In [152]:
```
replace_zeros_with_max_frequency_inplace(df, range(77, 78))
```

In [153]:
```
df['hand'].unique()
```

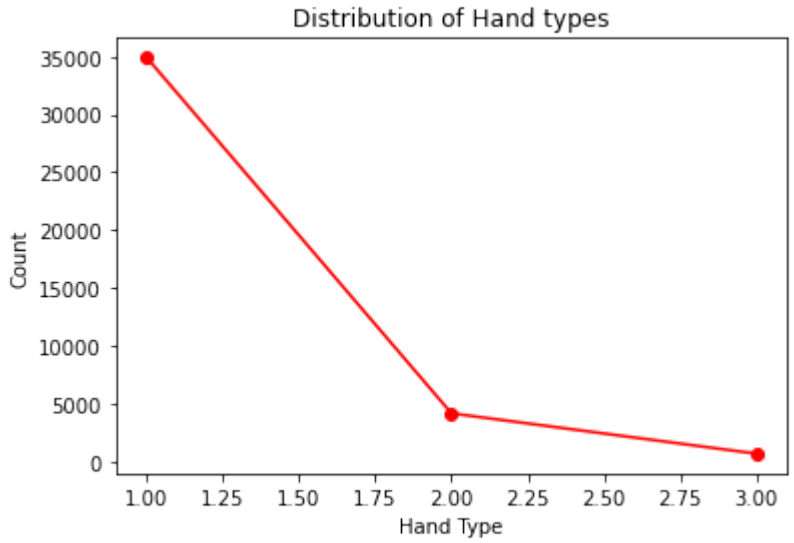
Out[153]:
```
array([1, 2, 3], dtype=int64)
```

In [154]:
```
df['hand'].value_counts()
```

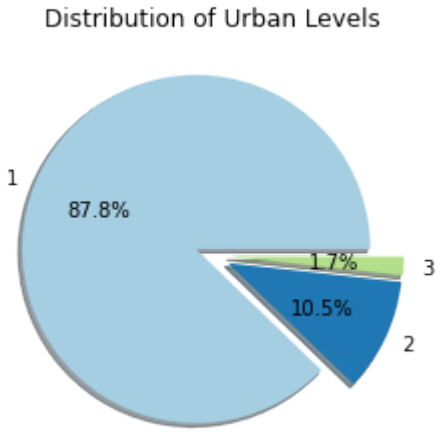
Out[154]:
```
1    34908
2     4171
3      689
Name: hand, dtype: int64
```

In [155]:
```
value_counts = df['hand'].value_counts().sort_index()
```

In [156]:
```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Hand Type')
plt.ylabel('Count')
plt.title('Distribution of Hand types')
plt.show()
```



In [157]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Urban Levels')
plt.show()
```



In [158]:
```
columns_to_check = df.columns[77:78]
plot_null_values(df, columns_to_check)
```

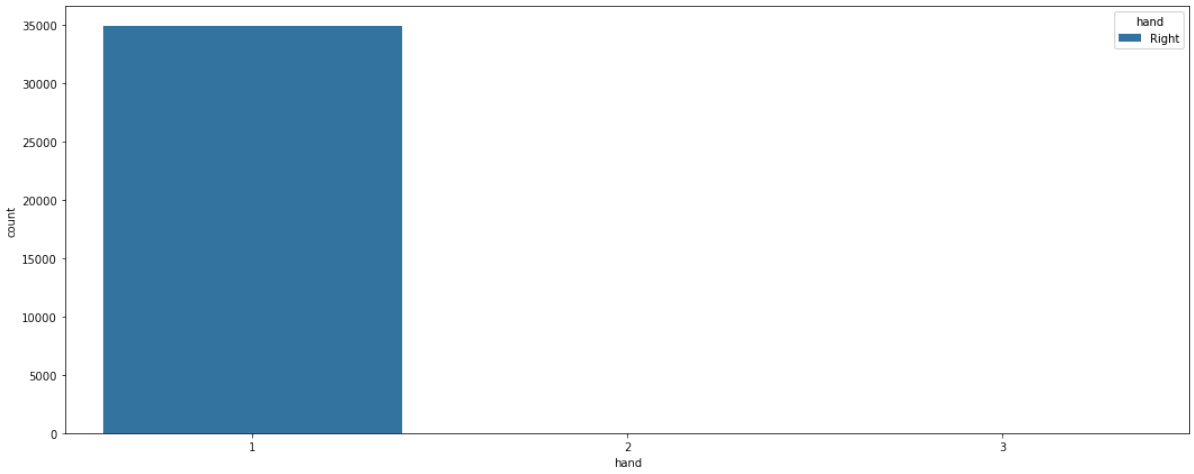
```
Null values in the specified columns:
       hand
0     False
1     False
2     False
3     False
4     False
...     ...
39770 False
39771 False
39772 False
39773 False
39774 False

[39768 rows x 1 columns]
```

In [159]:
```
def makeHandGroup(value):
    if value == 1:
        return 'Right'
    if  10 == 2:
        return 'Left'
    if 17 == 3:
        return 'Both'
```

In [160]:
```
hand_group = df['hand'].apply(makeHandGroup)
```

In [161]:
```
1 plt.figure(figsize=(18, 7))
2 sns.countplot(x=df['hand'], hue=hand_group)
```

Out[161]: <AxesSubplot:xlabel='hand', ylabel='count'>



in Religion Column

In [162]:
```
1 df.columns.get_loc('religion')
```

Out[162]: 78

In [163]:
```
1 df['religion'].unique()
```

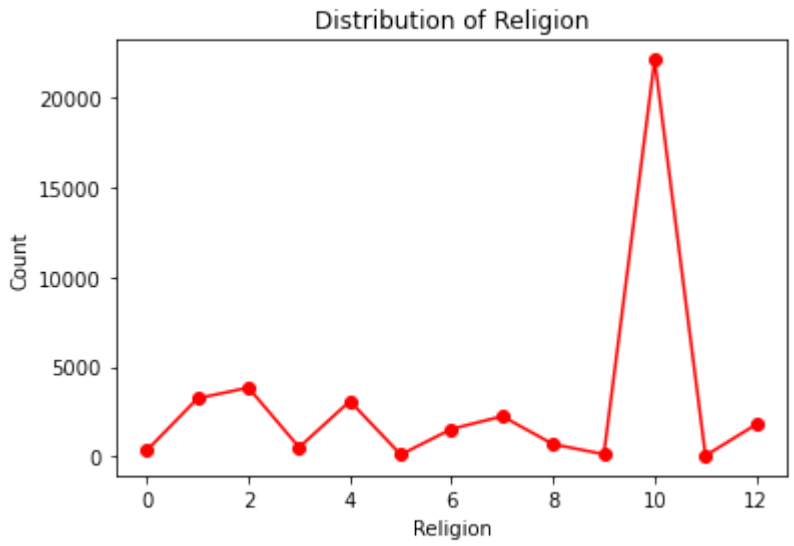
Out[163]: array([12, 7, 4, 10, 2, 6, 1, 8, 3, 0, 5, 11, 9], dtype=int64)

In [164]:
```
1 df['religion'].value_counts()
```

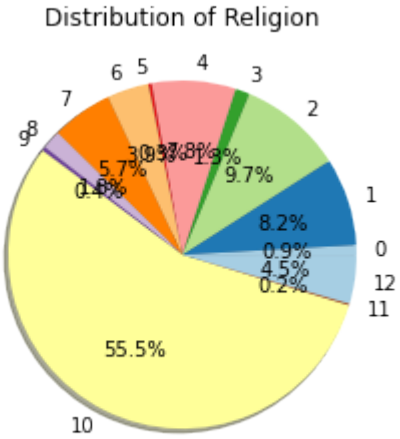
Out[164]:
```
10    22069
2      3844
1      3245
4      3096
7      2253
12     1804
6      1544
8       700
3       527
0       356
9       144
5       122
11       64
Name: religion, dtype: int64
```

In [165]:
```
1 value_counts = df['religion'].value_counts().sort_index()
```

In [166]:
```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Religion')
plt.ylabel('Count')
plt.title('Distribution of Religion')
plt.show()
```



In [167]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, autopct='%1.1f%%', shadow
plt.title('Distribution of Religion')
plt.show()
```



In [168]:
```
replace_zeros_with_max_frequency_inplace(df, range(78, 79))
```

In [169]:
```
df['religion'].unique()
```

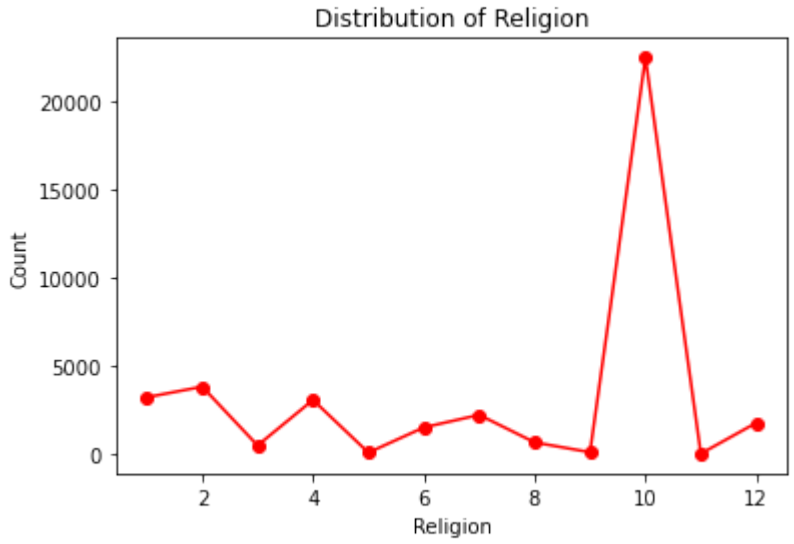
Out[169]:
```
array([12,  7,  4, 10,  2,  6,  1,  8,  3,  5, 11,  9], dtype=int64)
```

In [170]:
```
1 df['religion'].value_counts()
```

Out[170]:
```
10    22425
2      3844
1      3245
4      3096
7      2253
12     1804
6      1544
8       700
3       527
9       144
5       122
11       64
Name: religion, dtype: int64
```

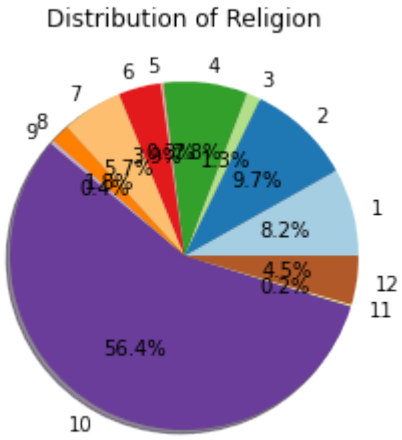
In [171]:
```
1 value_counts = df['religion'].value_counts().sort_index()
```

In [172]:
```
1 plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
2 plt.xlabel('Religion')
3 plt.ylabel('Count')
4 plt.title('Distribution of Religion')
5 plt.show()
```



In [173]:

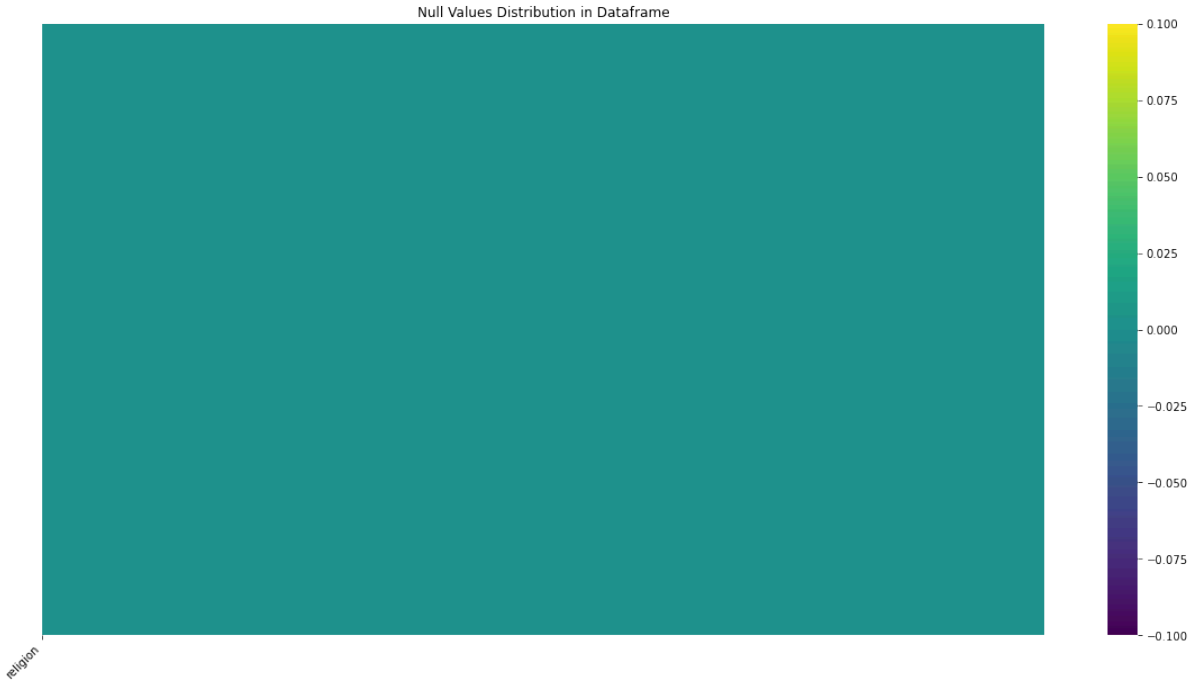
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, autopct='%1.1f%%', shadow
plt.title('Distribution of Religion')
plt.show()
```



In [174]:

```
columns_to_check = df.columns[78:79]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       religion
0         False
1         False
2         False
3         False
4         False
...         ...
39770     False
39771     False
39772     False
39773     False
39774     False

[39768 rows x 1 columns]
```

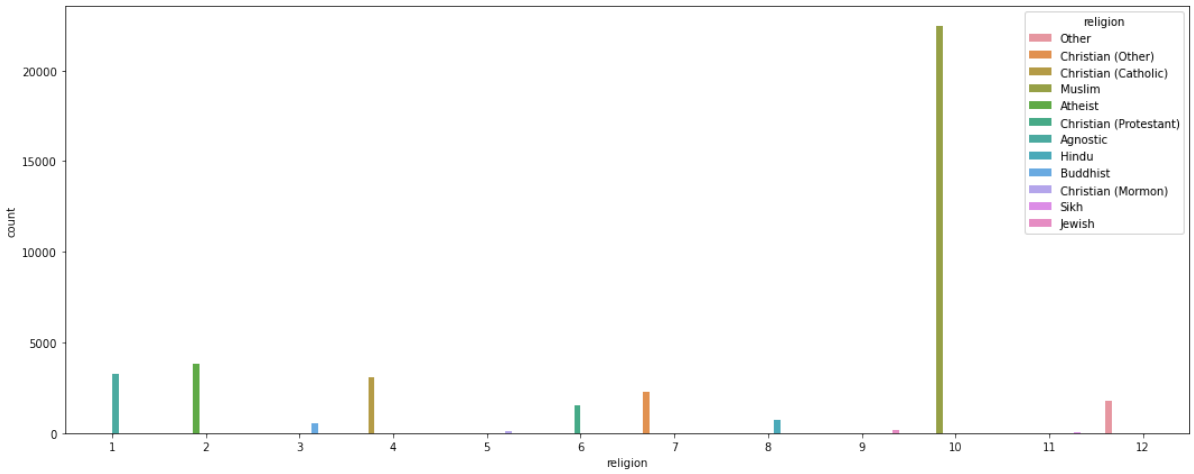


In [175]:
```
def makeReligiongroup(value):
    if value == 1:
        return 'Agnostic'
    if value == 2:
        return 'Atheist'
    if value == 3:
        return 'Buddhist'
    if value == 4:
        return 'Christian (Catholic)'
    if value == 5:
        return 'Christian (Mormon)'
    if value == 6:
        return 'Christian (Protestant)'
    if value == 7:
        return 'Christian (Other)'
    if value == 8:
        return 'Hindu'
    if value == 9:
        return 'Jewish'
    if value == 10:
        return 'Muslim'
    if value == 11:
        return 'Sikh'
    if value == 12:
        return 'Other'
```

In [176]:
```
religion = df['religion'].apply(makeReligiongroup)
```

In [177]:
```
plt.figure(figsize=(18, 7))
sns.countplot(x=df['religion'], hue=religion)
```

Out[177]: <AxesSubplot:xlabel='religion', ylabel='count'>



in Orientation Column

In [178]:
```
df.columns.get_loc('orientation')
```

Out[178]: 79

In [179]:
```
1 df['orientation'].unique()
```

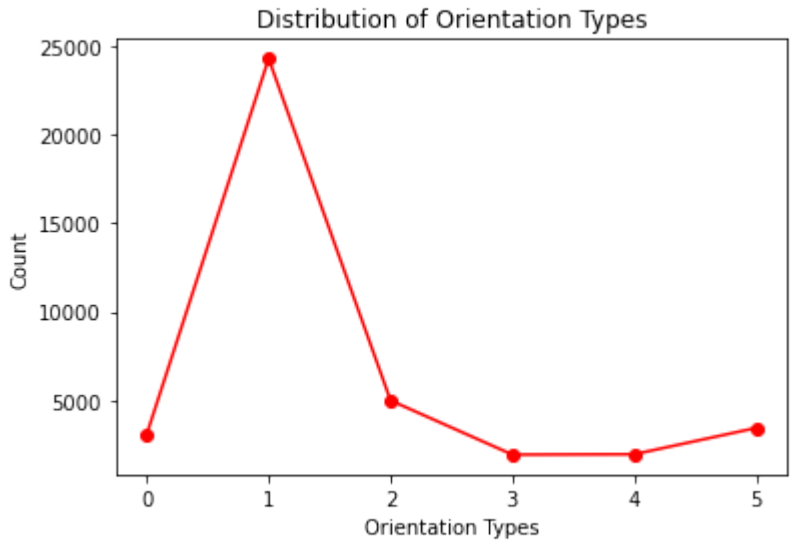
Out[179]:
```
array([1, 0, 3, 5, 2, 4], dtype=int64)
```

In [180]:
```
1 df['orientation'].value_counts()
```

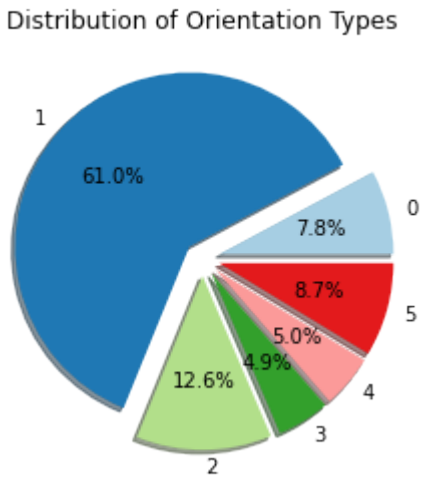
Out[180]:
```
1    24266
2     5006
5     3459
0     3109
4     1975
3     1953
Name: orientation, dtype: int64
```

In [181]:
```
1 value_counts = df['orientation'].value_counts().sort_index()
```

In [182]:
```
1 plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
2 plt.xlabel('Orientation Types')
3 plt.ylabel('Count')
4 plt.title('Distribution of Orientation Types')
5 plt.show()
```



In [183]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Orientation Types')
plt.show()
```



In [184]:
```
replace_zeros_with_max_frequency_inplace(df, range(79, 80))
```

In [185]:
```
df['orientation'].unique()
```

Out[185]:
```
array([1, 3, 5, 2, 4], dtype=int64)
```

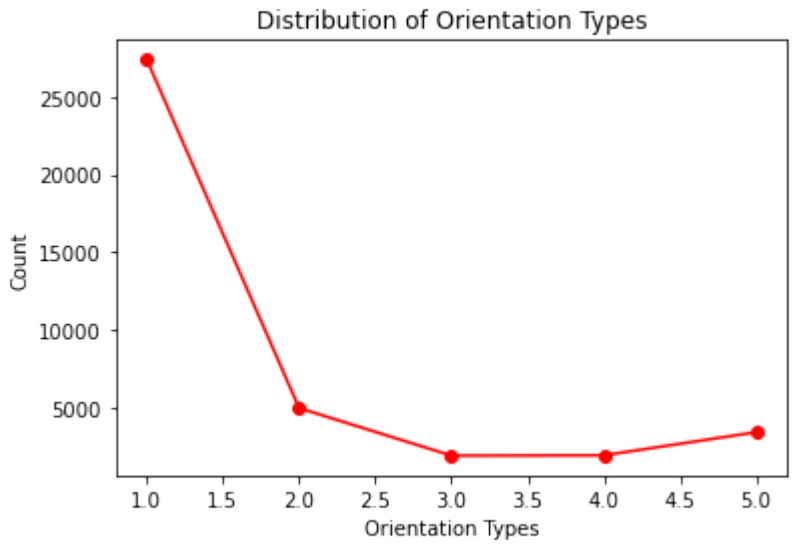
In [186]:
```
df['orientation'].value_counts()
```

Out[186]:
```
1    27375
2     5006
5     3459
4     1975
3     1953
Name: orientation, dtype: int64
```

In [187]:
```
value_counts = df['orientation'].value_counts().sort_index()
```

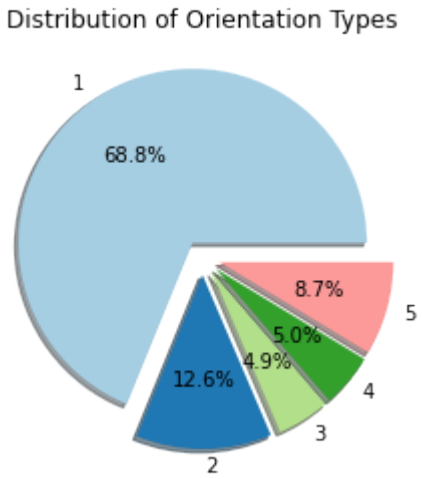
In [188]:

```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Orientation Types')
plt.ylabel('Count')
plt.title('Distribution of Orientation Types')
plt.show()
```



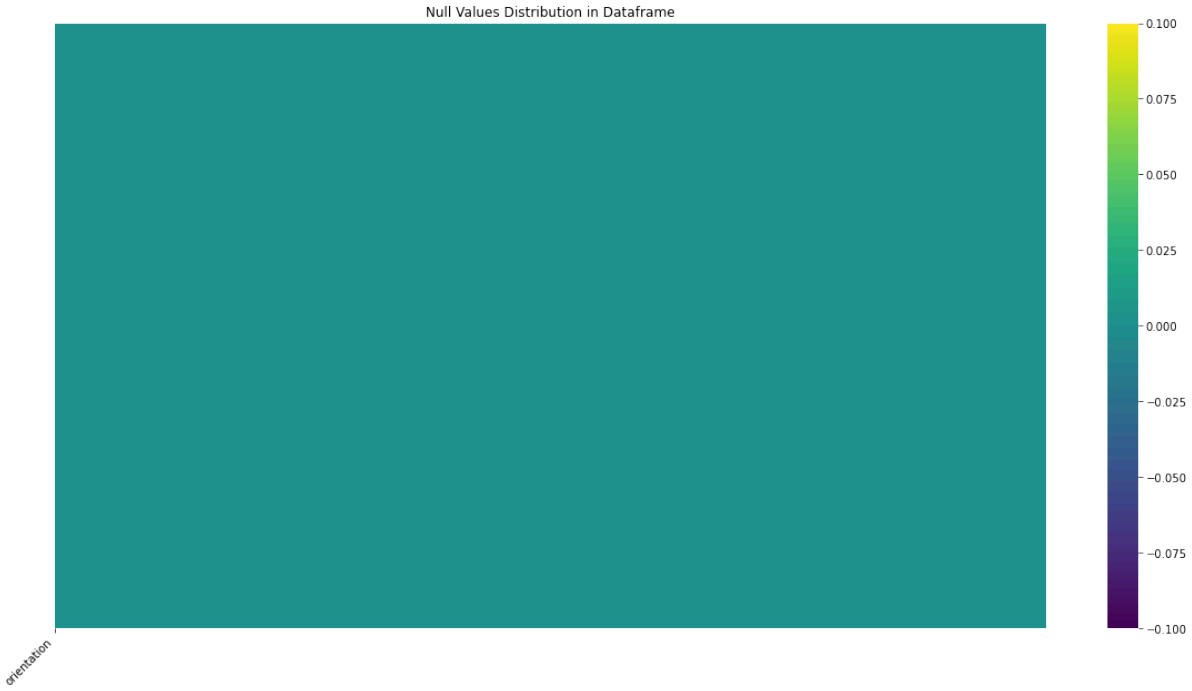
In [189]:

```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Orientation Types')
plt.show()
```



In [190]:
```
columns_to_check = df.columns[79:80]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       orientation
0            False
1            False
2            False
3            False
4            False
...            ...
39770        False
39771        False
39772        False
39773        False
39774        False

[39768 rows x 1 columns]
```

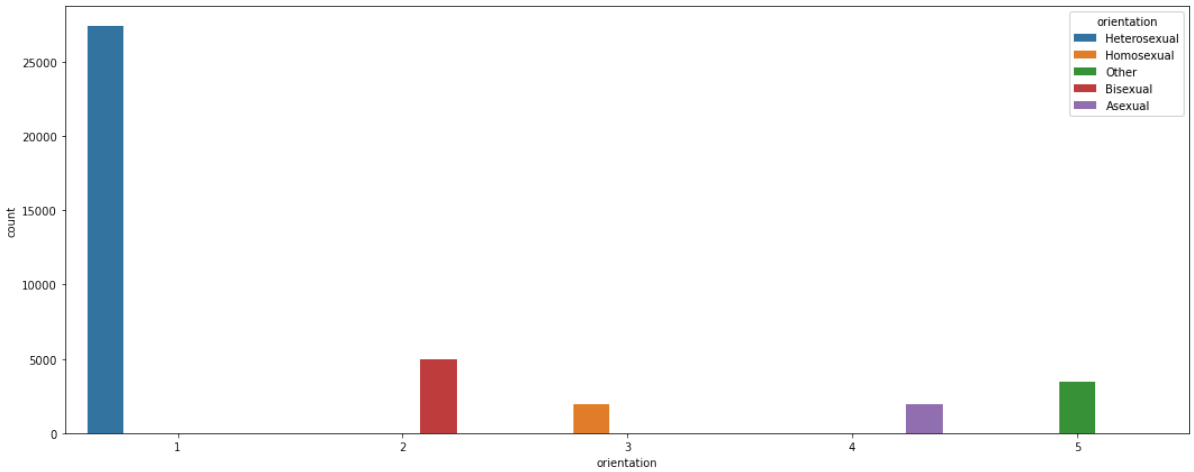


In [191]:
```
def makeOrientationGroup(value):
    if value == 1:
        return 'Heterosexual'
    if value == 2:
        return 'Bisexual'
    if value == 3:
        return 'Homosexual'
    if value == 4:
        return 'Asexual'
    if value == 5:
        return 'Other'
```

In [192]:
```
1 orientation = df['orientation'].apply(makeOrientationGroup)
```

In [193]:
```
1 plt.figure(figsize=(18, 7))
2 sns.countplot(x=df['orientation'], hue=orientation)
```

Out[193]: <AxesSubplot:xlabel='orientation', ylabel='count'>



in Race Column

In [194]:
```
1 df.columns.get_loc('race')
```

Out[194]: 80

In [195]:
```
1 df['race'].unique()
```

Out[195]: array([10, 70, 60, 50, 30, 40, 20], dtype=int64)

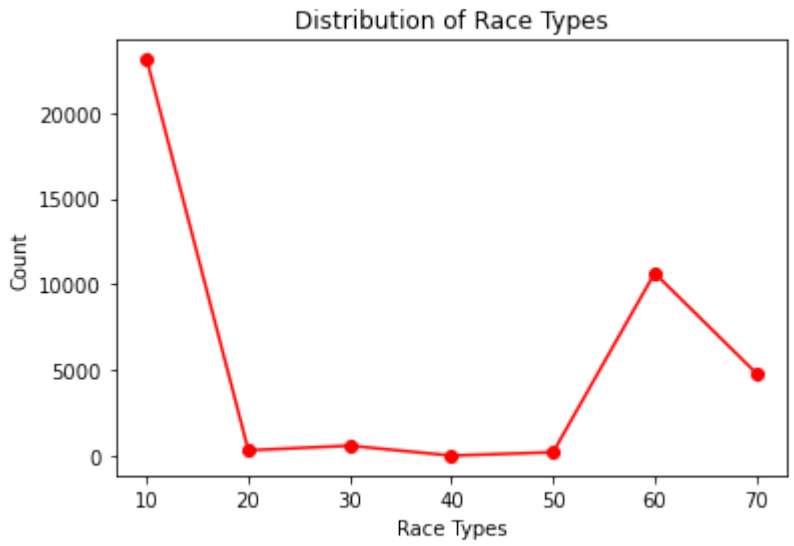
In [196]:
```
1 df['race'].value_counts()
```

Out[196]:
```
10    23101
60    10658
70     4831
30      603
20      333
50      220
40       22
Name: race, dtype: int64
```

In [197]:
```
1 value_counts = df['race'].value_counts().sort_index()
```

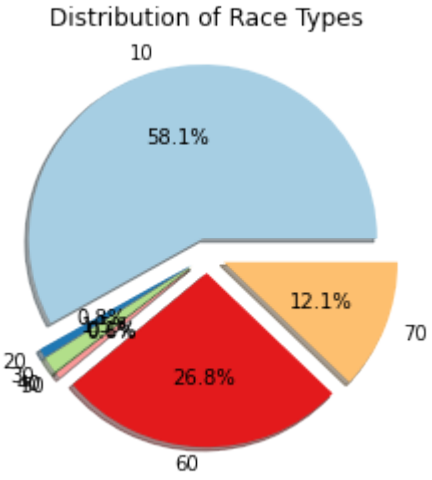
In [198]:

```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Race Types')
plt.ylabel('Count')
plt.title('Distribution of Race Types')
plt.show()
```



In [199]:

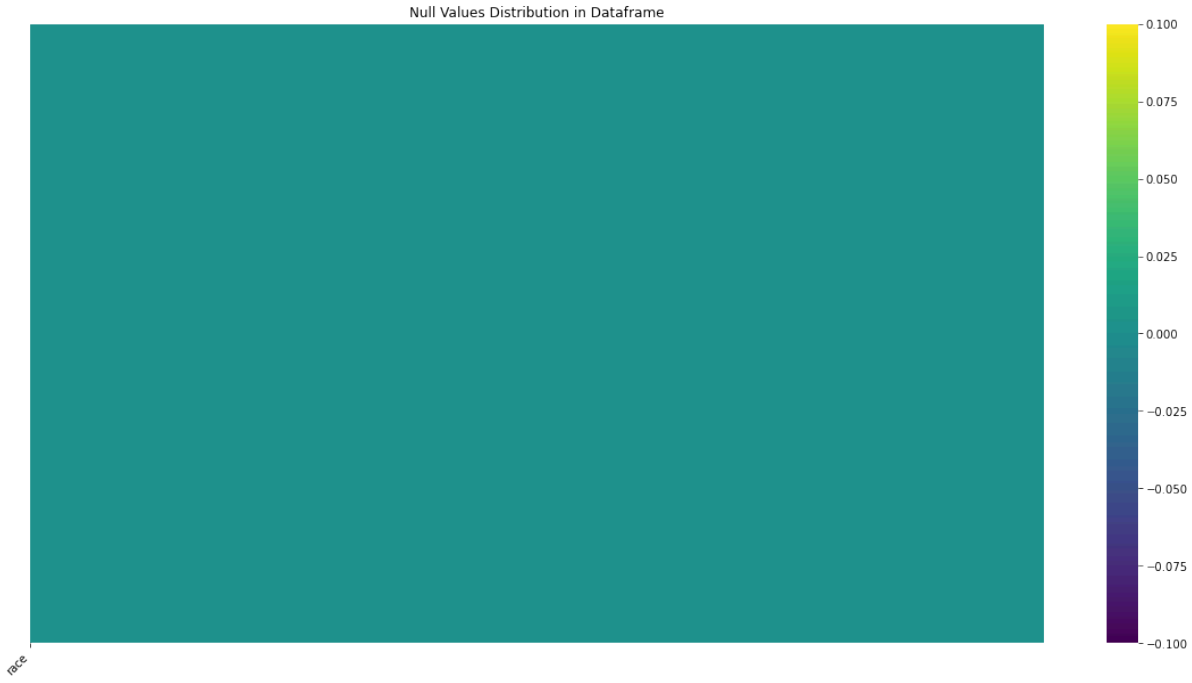
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Race Types')
plt.show()
```



In [200]:

```
columns_to_check = df.columns[80:81]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
        race
0      False
1      False
2      False
3      False
4      False
...      ...
39770  False
39771  False
39772  False
39773  False
39774  False

[39768 rows x 1 columns]
```

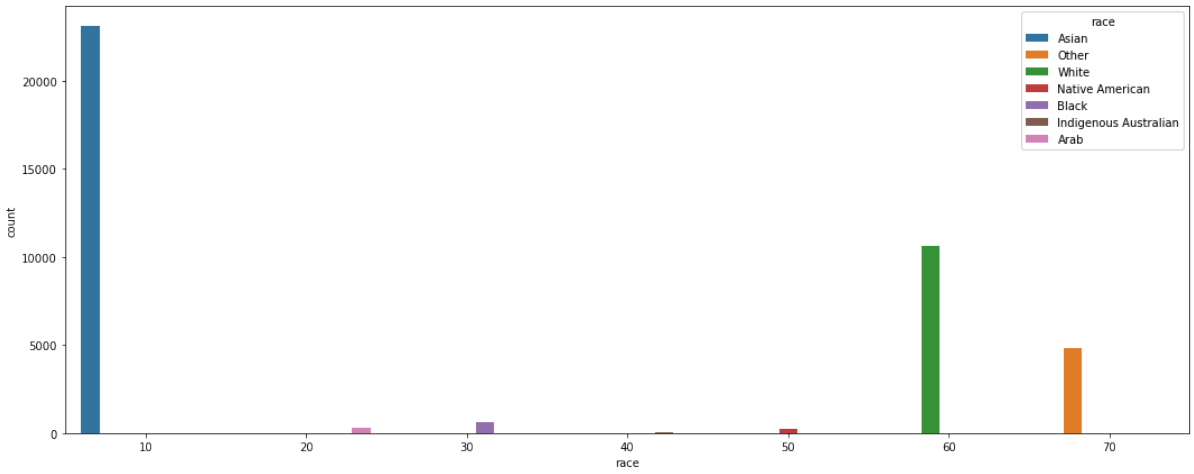


In [201]:
```
def makeRaceGroup(value):
    if value == 10:
        return 'Asian'
    if value == 20:
        return 'Arab'
    if value == 30:
        return 'Black'
    if value == 40:
        return 'Indigenous Australian'
    if value == 50:
        return 'Native American'
    if value == 60:
        return 'White'
    if value == 70:
        return 'Other'
```

In [202]:
```
race = df['race'].apply(makeRaceGroup)
```

In [203]:
```
plt.figure(figsize=(18, 7))
sns.countplot(x=df['race'], hue=race)
```

Out[203]: <AxesSubplot:xlabel='race', ylabel='count'>



in Voted column

In [204]:
```
df.columns.get_loc('voted')
```

Out[204]: 81

In [205]:
```
df['voted'].unique()
```

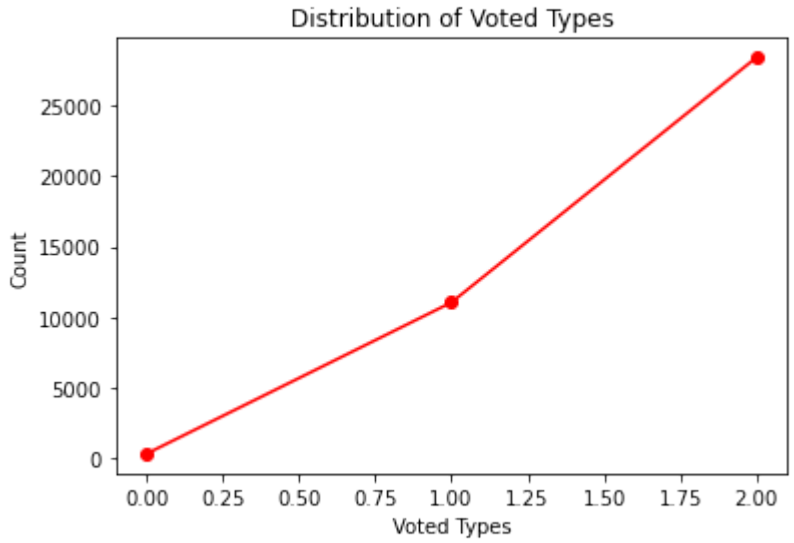
Out[205]: array([2, 1, 0], dtype=int64)

In [206]:
```
df['voted'].value_counts()
```

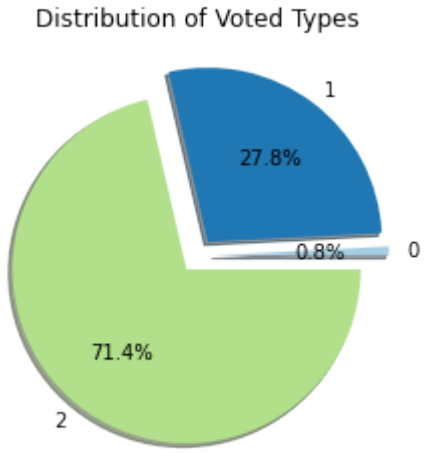
Out[206]:
```
2    28393
1    11048
0      327
Name: voted, dtype: int64
```

In [207]:
```
value_counts = df['voted'].value_counts().sort_index()
```

In [208]:
```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Voted Types')
plt.ylabel('Count')
plt.title('Distribution of Voted Types')
plt.show()
```



In [209]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Voted Types')
plt.show()
```



In [210]:
```
1 replace_zeros_with_max_frequency_inplace(df, range(81, 82))
```

In [211]:
```
1 df['voted'].unique()
```

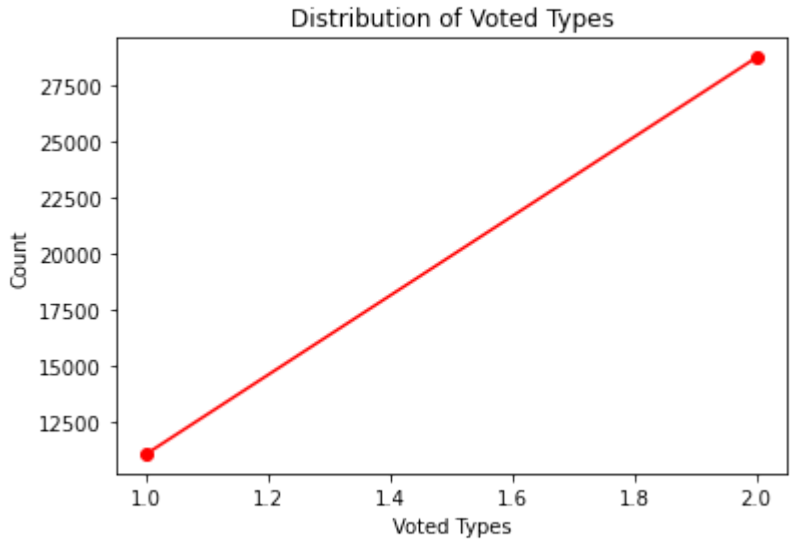
Out[211]:
```
array([2, 1], dtype=int64)
```

In [212]:
```
1 df['voted'].value_counts()
```

Out[212]:
```
2    28720
1    11048
Name: voted, dtype: int64
```

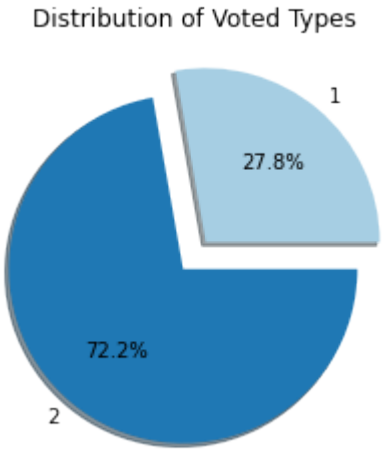
In [213]:
```
1 value_counts = df['voted'].value_counts().sort_index()
```

In [214]:
```
1 plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
2 plt.xlabel('Voted Types')
3 plt.ylabel('Count')
4 plt.title('Distribution of Voted Types')
5 plt.show()
```



In [215]:

```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Voted Types')
plt.show()
```



In [216]:
```
columns_to_check = df.columns[81:82]
plot_null_values(df, columns_to_check)
```

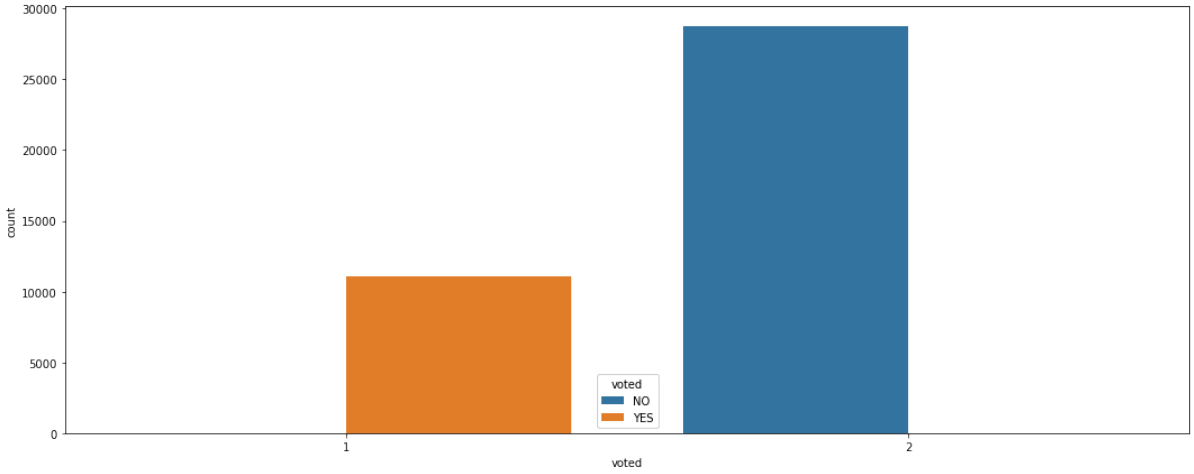
```
Null values in the specified columns:
       voted
0      False
1      False
2      False
3      False
4      False
...      ...
39770  False
39771  False
39772  False
39773  False
39774  False

[39768 rows x 1 columns]
```

In [217]:
```
def makeVotedGroup(value):
    if value == 1:
        return 'YES'
    if value == 2:
        return 'NO'
```

In [218]:
```
voted = df['voted'].apply(makeVotedGroup)
```

In [219]:
```
plt.figure(figsize=(18, 7))
sns.countplot(x=df['voted'], hue=voted)
```

Out[219]: <AxesSubplot:xlabel='voted', ylabel='count'>



in Married column

In [220]:
```
df.columns.get_loc('married')
```

Out[220]: 82

In [221]:
```
df['married'].unique()
```

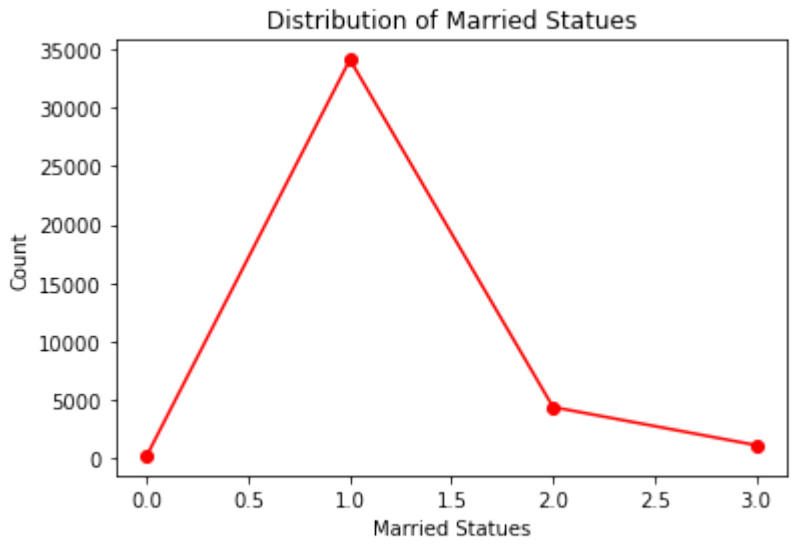
Out[221]: array([1, 3, 2, 0], dtype=int64)

In [222]:
```
df['married'].value_counts()
```

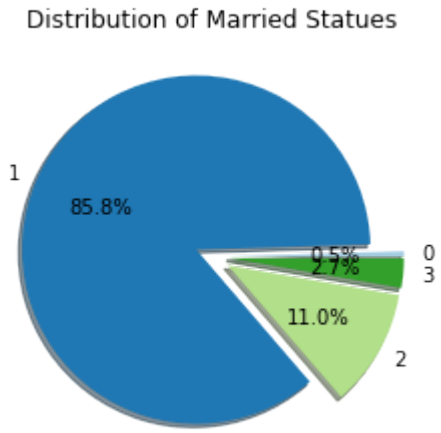
Out[222]:
```
1    34125
2     4356
3     1092
0      195
Name: married, dtype: int64
```

In [223]:
```
value_counts = df['married'].value_counts().sort_index()
```

In [224]:
```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Married Statues')
plt.ylabel('Count')
plt.title('Distribution of Married Statues')
plt.show()
```



In [225]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Married Statues')
plt.show()
```



In [226]:
```
replace_zeros_with_max_frequency_inplace(df, range(82, 83))
```

In [227]:
```
df['married'].unique()
```

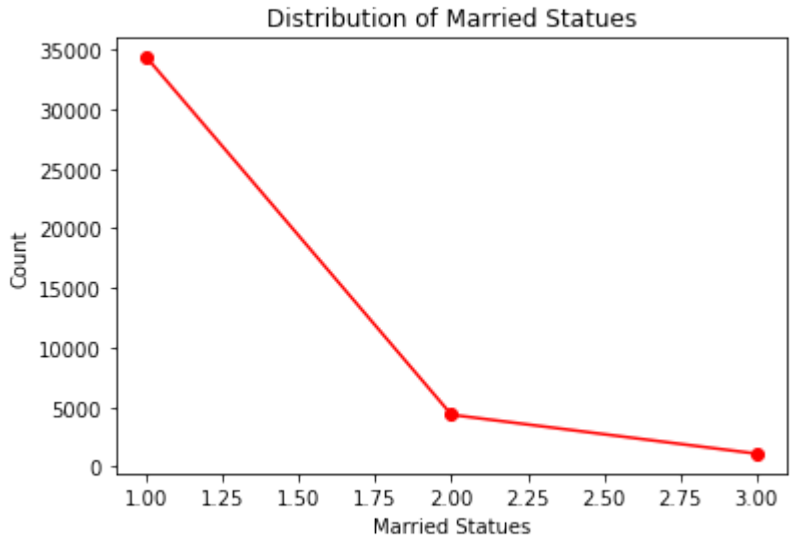
Out[227]:
```
array([1, 3, 2], dtype=int64)
```

In [228]:
```
1  df['married'].value_counts()
```

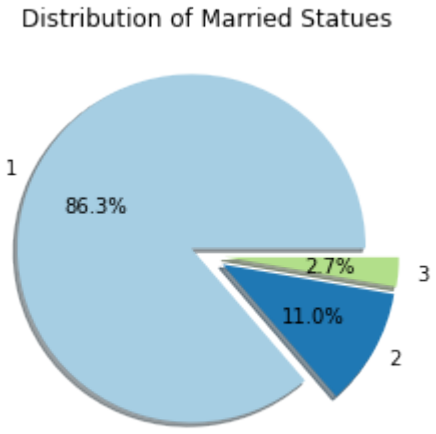
Out[228]:
```
1    34320
2     4356
3     1092
Name: married, dtype: int64
```

In [229]:
```
1  value_counts = df['married'].value_counts().sort_index()
```

In [230]:
```
1  plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
2  plt.xlabel('Married Statues')
3  plt.ylabel('Count')
4  plt.title('Distribution of Married Statues')
5  plt.show()
```

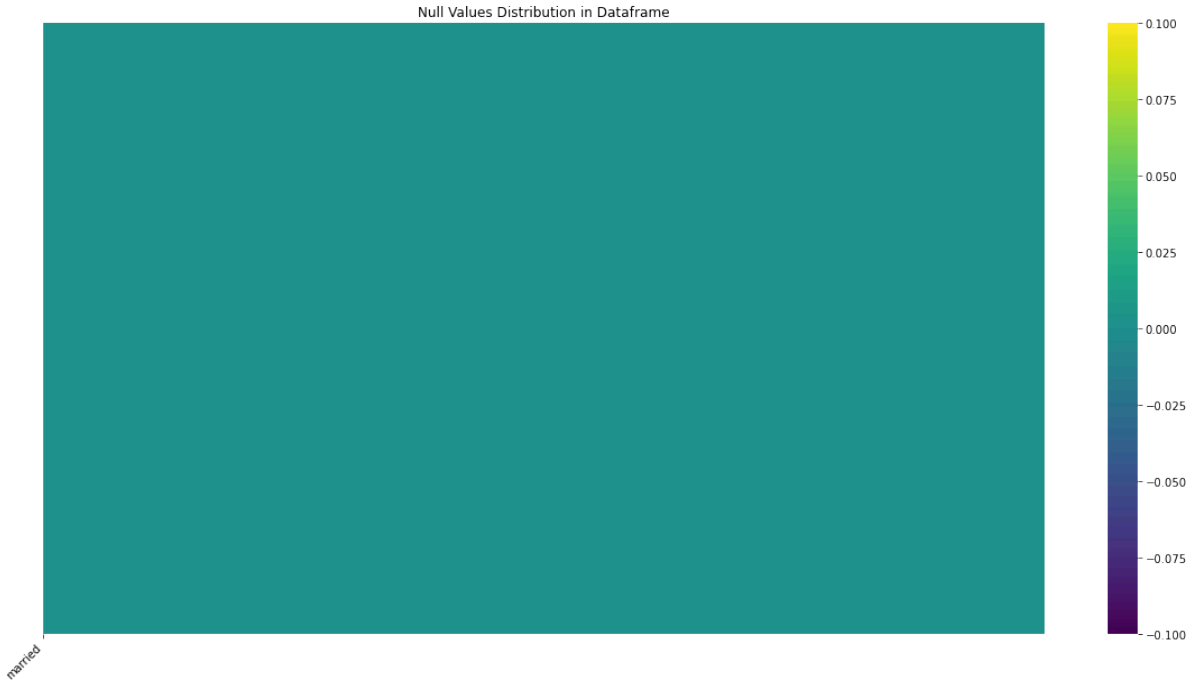


In [231]:
```
1  explode_values = [0.1] * len(value_counts)
2  plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
3  plt.title('Distribution of Married Statues')
4  plt.show()
```



In [232]:
```
columns_to_check = df.columns[82:83]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       married
0        False
1        False
2        False
3        False
4        False
...        ...
39770    False
39771    False
39772    False
39773    False
39774    False

[39768 rows x 1 columns]
```

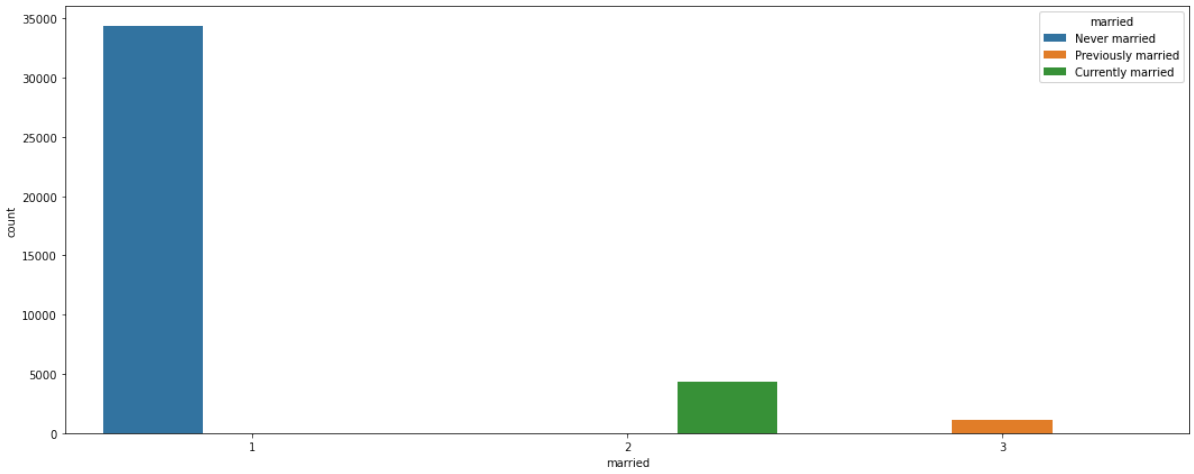


In [233]:
```
def makeMarriedGroup(value):
    if value == 1:
        return 'Never married'
    if value == 2:
        return 'Currently married'
    if value == 3:
        return 'Previously married'
```

In [234]:
```
married = df['married'].apply(makeMarriedGroup)
```

In [235]:
```
1 plt.figure(figsize=(18, 7))
2 sns.countplot(x=df['married'], hue=married)
```

Out[235]: <AxesSubplot:xlabel='married', ylabel='count'>



in Familysize Column

In [236]:
```
1 df.columns.get_loc('familysize')
```

Out[236]: 83

In [237]:
```
1 df['familysize'].unique()
```

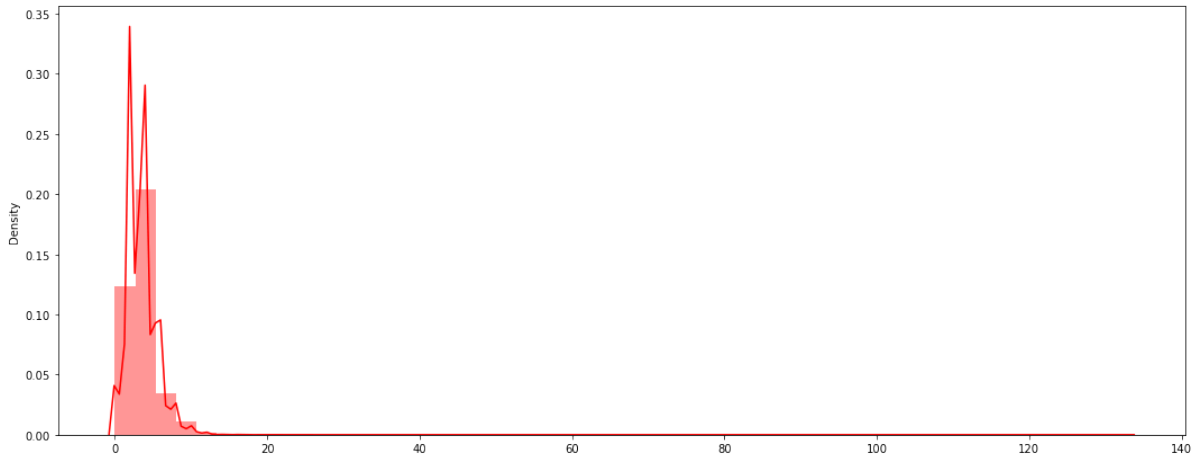
Out[237]:
```
array([  2,   4,   3,   5,   1,   6,   8,  12,   7,   0,  11,   9,  13,
        10,  62,  16,  14,  99,  17,  54,  65,  15,  26,  24,  19,  21,
        23, 133], dtype=int64)
```

In [238]:
```
1 df['familysize'].value_counts()
```

Out[238]:
```
3      9204
2      9016
4      7538
5      4829
1      2946
6      2449
7      1243
0      1125
8       676
9       331
10      195
11      109
12       56
13       19
14        8
15        6
16        5
17        3
24        1
23        1
21        1
19        1
62        1
26        1
65        1
54        1
99        1
133       1
Name: familysize, dtype: int64
```

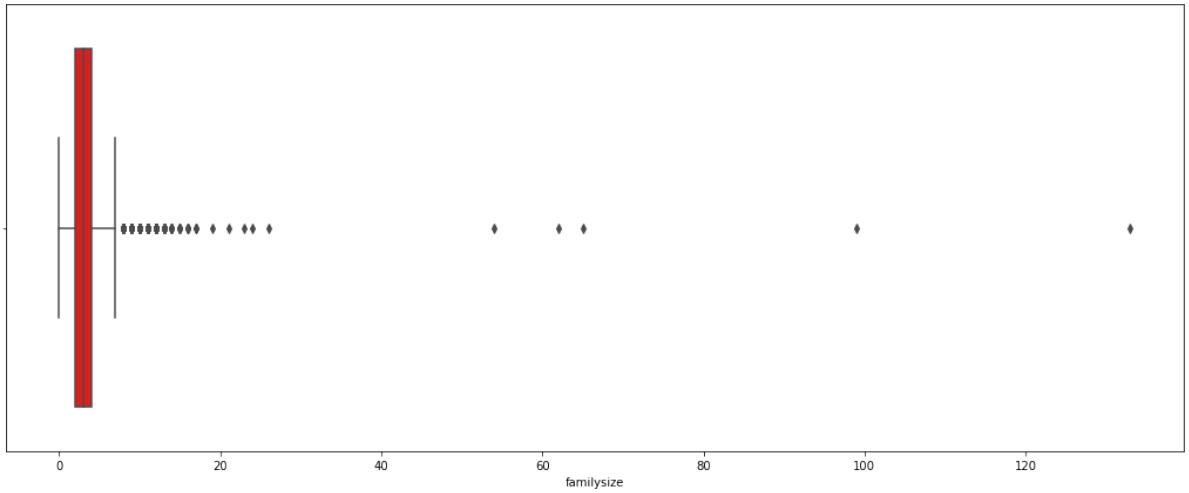
In [239]:
```
1 plt.figure(figsize=(18, 7))
2 sns.distplot(x=df['familysize'], color='red')
```

Out[239]:
```
<AxesSubplot:ylabel='Density'>
```



In [240]:
```
plt.figure(figsize=(18, 7))
sns.boxplot(x=df['familysize'], color='red')
```

Out[240]: <AxesSubplot:xlabel='familysize'>



In [241]:
```
familysize_indexes = df[df['familysize'] > 15]['familysize'].index
display(familysize_indexes)
print(f'DataFrame size before: {df.shape[0]}')
df = df.drop(familysize_indexes, axis=0)
print(f'DataFrame size after: {df.shape[0]}')
```

```
Int64Index([ 1174,  2137,  6550, 16897, 17452, 17512, 17682, 18026, 18268,
            19781, 20779, 21771, 29800, 33483, 34247, 34522, 34829, 34901],
           dtype='int64')

DataFrame size before: 39768
DataFrame size after: 39750
```

In [242]:
```
df['familysize'].unique()
```

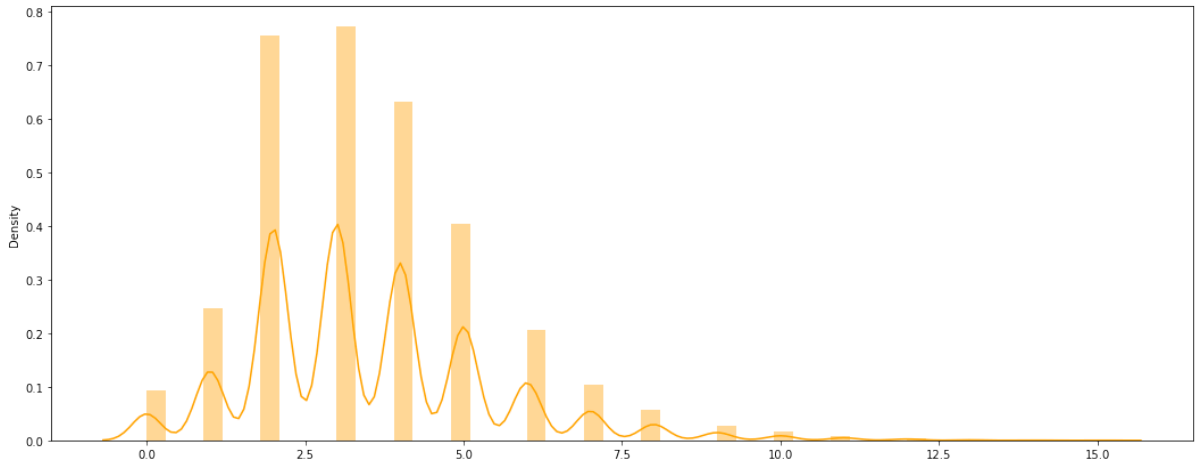
Out[242]:
```
array([ 2,  4,  3,  5,  1,  6,  8, 12,  7,  0, 11,  9, 13, 10, 14, 15],
      dtype=int64)
```

In [243]:
```
1 df['familysize'].value_counts()
```

Out[243]:
```
3     9204
2     9016
4     7538
5     4829
1     2946
6     2449
7     1243
0     1125
8      676
9      331
10     195
11     109
12      56
13      19
14       8
15       6
Name: familysize, dtype: int64
```

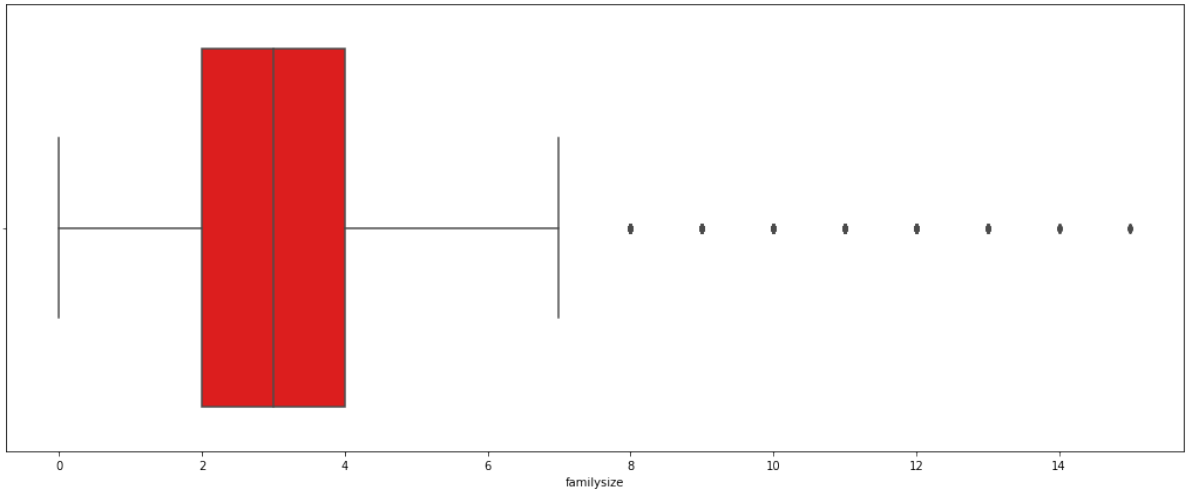
In [244]:
```
1 plt.figure(figsize=(18, 7))
2 sns.distplot(x=df['familysize'], color='orange')
```

Out[244]:
```
<AxesSubplot:ylabel='Density'>
```



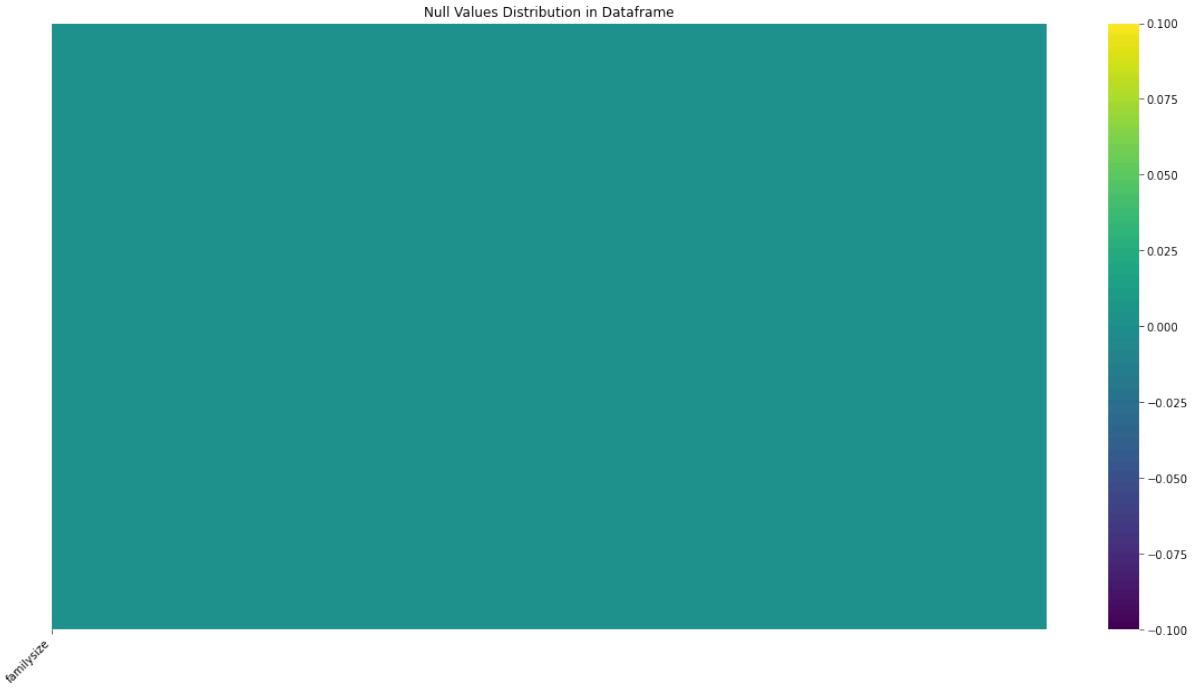
In [245]:
```
1 plt.figure(figsize=(18, 7))
2 sns.boxplot(x=df['familysize'], color='red')
```

Out[245]: <AxesSubplot:xlabel='familysize'>



In [246]:
```
columns_to_check = df.columns[83:84]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       familysize
0           False
1           False
2           False
3           False
4           False
...           ...
39770       False
39771       False
39772       False
39773       False
39774       False

[39750 rows x 1 columns]
```



in Country Column

In [247]:
```
df.columns.get_loc('country')
```

Out[247]: 42

In [248]:
```
1 df['country'].unique()
```

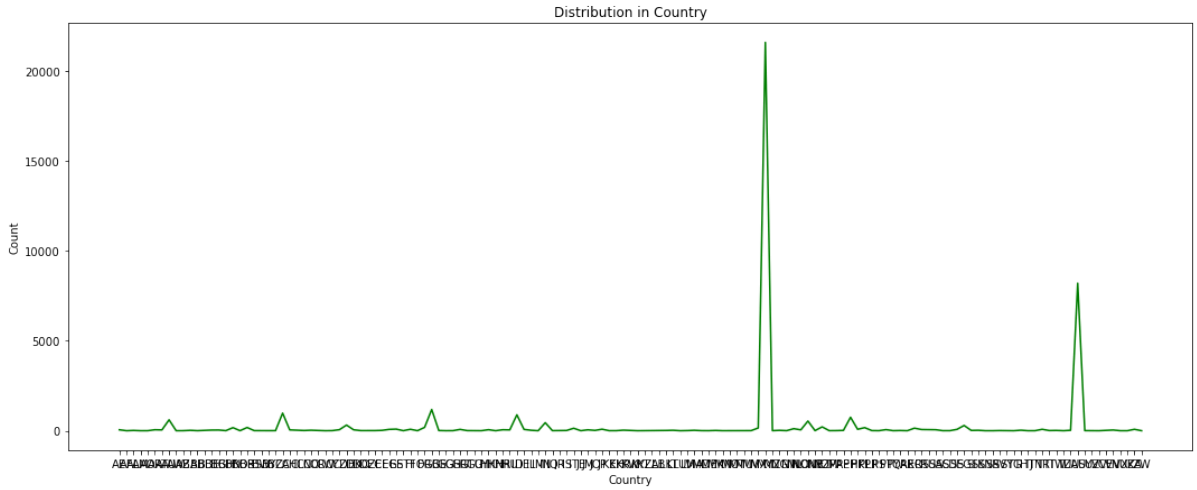
Out[248]:
```
array(['IN', 'US', 'PL', 'MY', 'MX', 'GB', 'DE', 'EE', 'CA', 'EC', 'AU',
       'FI', 'ID', 'AE', 'NONE', 'ES', 'NI', 'DO', 'TR', 'NO', 'GR', 'LK',
       'BR', 'AR', 'KH', 'IT', 'MK', 'PT', 'BA', 'RU', 'HU', 'KR', 'IE',
       'RS', 'CZ', 'PH', 'RO', 'FR', 'SG', 'AT', 'UA', 'KW', 'CO', 'GE',
       'SE', 'HK', 'NZ', 'ZA', 'NL', 'DK', 'JM', 'LB', 'CL', 'AW', 'IL',
       'GT', 'PE', 'PK', 'NP', 'HR', 'CR', 'VE', 'BG', 'GH', 'MA', 'PR',
       'SI', 'LV', 'AL', 'VN', 'GU', 'BD', 'TH', 'NG', 'FO', 'UY', 'EG',
       'BE', 'SA', 'SV', 'CH', 'PY', 'SK', 'SY', 'TN', 'TT', 'SR', 'KE',
       'BY', 'PA', 'CY', 'BW', 'MZ', 'BB', 'GG', 'CW', 'IS', 'IR', 'BN',
       'MV', 'OM', 'DZ', 'JP', 'MU', nan, 'IQ', 'BO', 'MD', 'CN', 'LT',
       'BZ', 'BH', 'ME', 'QA', 'TW', 'PS', 'JO', 'SD', 'KY', 'AZ', 'AO',
       'BS', 'GY', 'MO', 'TZ', 'IM', 'AF', 'AM', 'UZ', 'LU', 'ET', 'JE',
       'VU', 'TJ', 'KZ', 'XK', 'HN', 'ZW', 'LA', 'MT', 'SN', 'MN', 'TG',
       'SC', 'RE', 'VC'], dtype=object)
```

In [249]:
```
1 df['country'].value_counts()
```

Out[249]:
```
MY    21589
US     8203
GB     1179
CA      978
ID      884
      ...
UZ        1
AM        1
AF        1
IM        1
VC        1
Name: country, Length: 145, dtype: int64
```

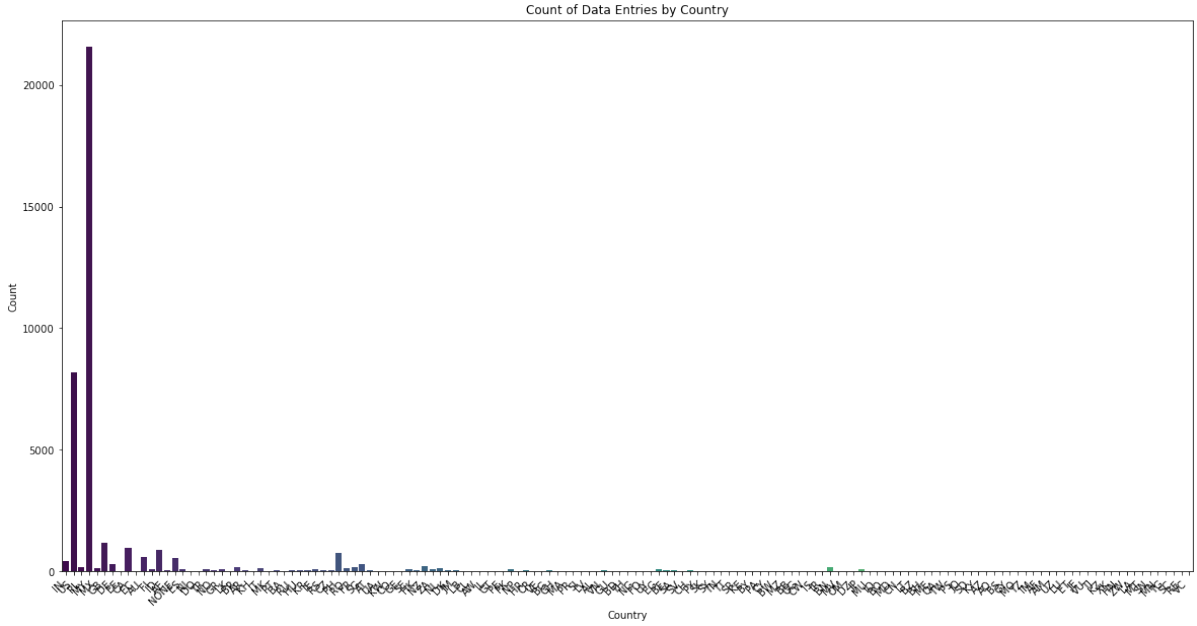
In [250]:
```
1 value_counts = df['country'].value_counts().sort_index()
```

In [251]:
```
1 plt.figure(figsize=(18, 7))
2 plt.plot(value_counts.index, value_counts.values, color='g')
3 plt.xlabel('Country')
4 plt.ylabel('Count')
5 plt.title('Distribution in Country')
6 plt.show()
```



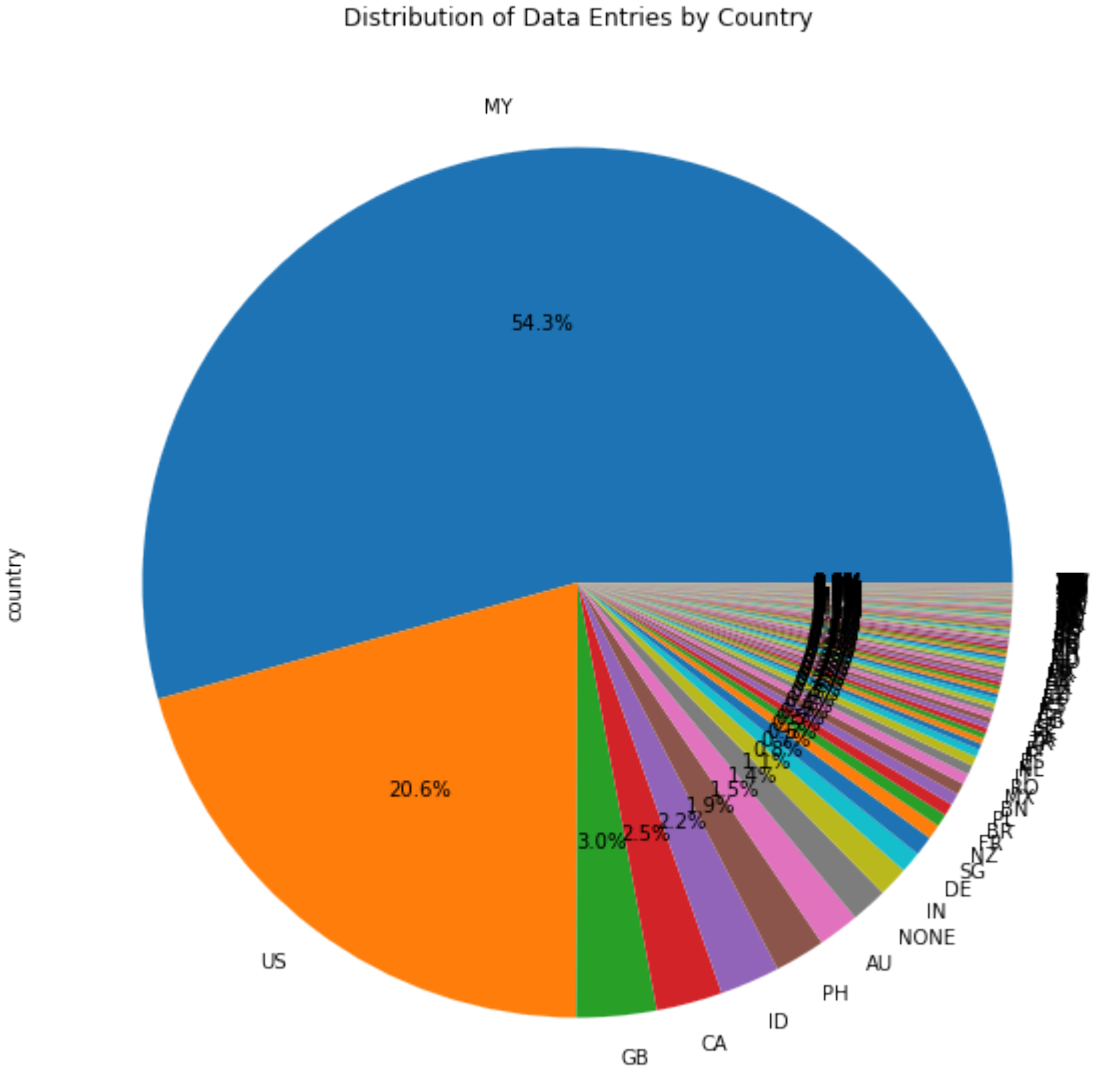
In [252]:

```
plt.figure(figsize=(20, 10))
sns.countplot(x=df['country'], data=df, palette='viridis')
plt.title('Count of Data Entries by Country')
plt.xlabel('Country')
plt.ylabel('Count')
plt.xticks(rotation=45, ha='right')
plt.show()
```



In [253]:

```
plt.figure(figsize=(10, 10))
df['country'].value_counts().plot.pie(autopct='%1.1f%%', startangle=0)
plt.title('Distribution of Data Entries by Country')
plt.show()
```



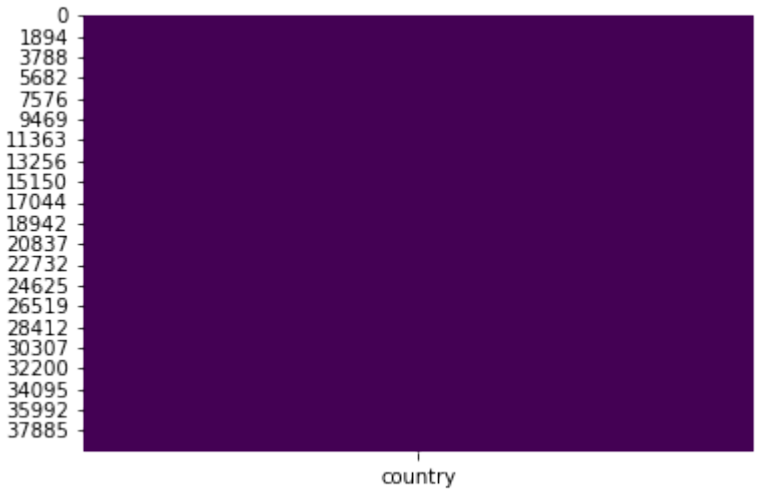
In [254]:

```
nan_values = df['country'].isnull().sum()
print(f"Number of NaN values in the 'country' column: {nan_values}")
```

```
Number of NaN values in the 'country' column: 2
```

In [255]:
```
1 sns.heatmap(df[['country']].isnull(), cbar=False, cmap='viridis')
```

Out[255]: <AxesSubplot:>



In [256]:
```
1 most_frequent_country = df['country'].value_counts().idxmax()
2 most_frequent_country
```

Out[256]: 'MY'

In [257]:
```
1 df['country'].fillna(most_frequent_country, inplace=True)
```

In [258]:
```
1 print("NaN values in 'country' column after filling:")
2 print(df['country'].isnull().sum())
```

```
NaN values in 'country' column after filling:
0
```

in Screensize Column

In [259]:
```
1 df.columns.get_loc('screensize')
```

Out[259]: 75

In [260]:
```
1 df['screensize'].unique()
```

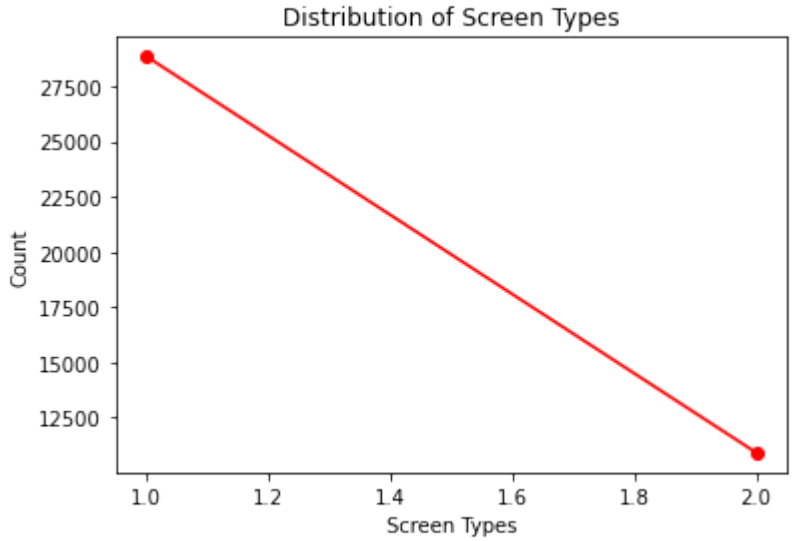
Out[260]: array([1, 2], dtype=int64)

In [261]:
```
1 df['orientation'].value_counts()
```

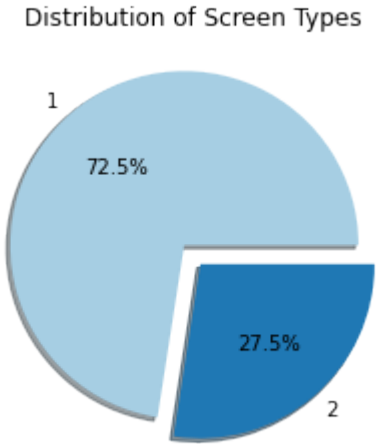
Out[261]:
```
1    27367
2     5004
5     3453
4     1974
3     1952
Name: orientation, dtype: int64
```

In [262]:
```
value_counts = df['screensize'].value_counts().sort_index()
```

In [263]:
```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Screen Types')
plt.ylabel('Count')
plt.title('Distribution of Screen Types')
plt.show()
```

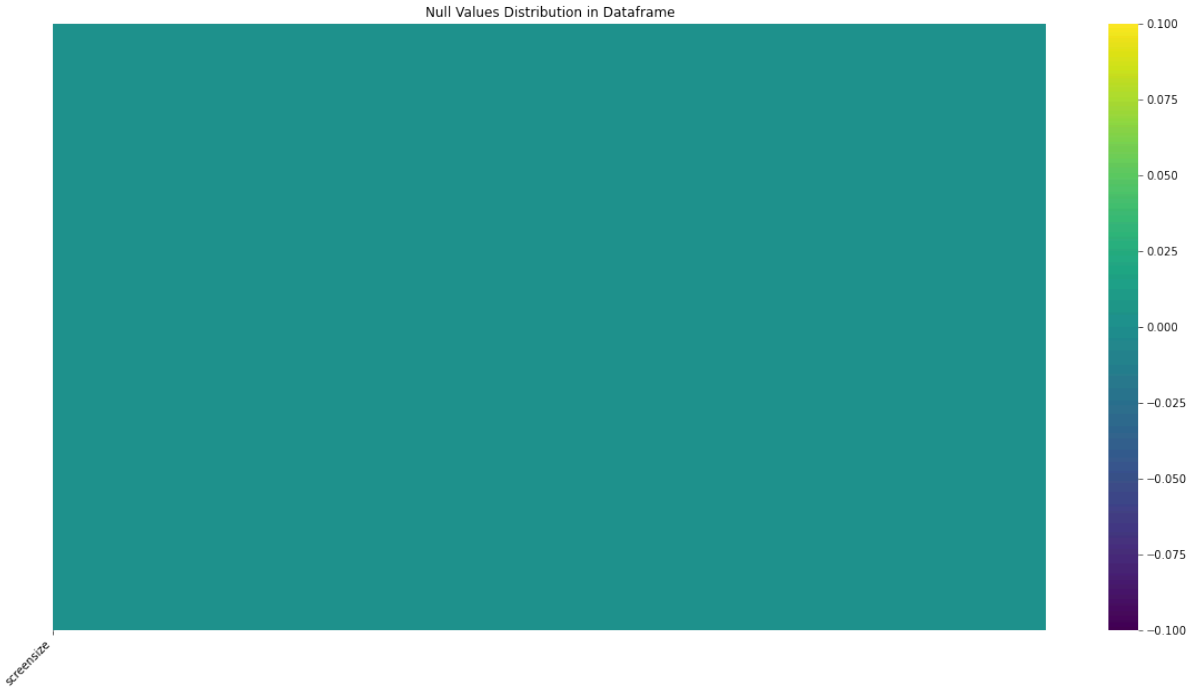


In [264]:
```
explode_values = [0.071] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Screen Types')
plt.show()
```



In [265]:
```
columns_to_check = df.columns[75:76]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       screensize
0           False
1           False
2           False
3           False
4           False
...           ...
39770       False
39771       False
39772       False
39773       False
39774       False

[39750 rows x 1 columns]
```

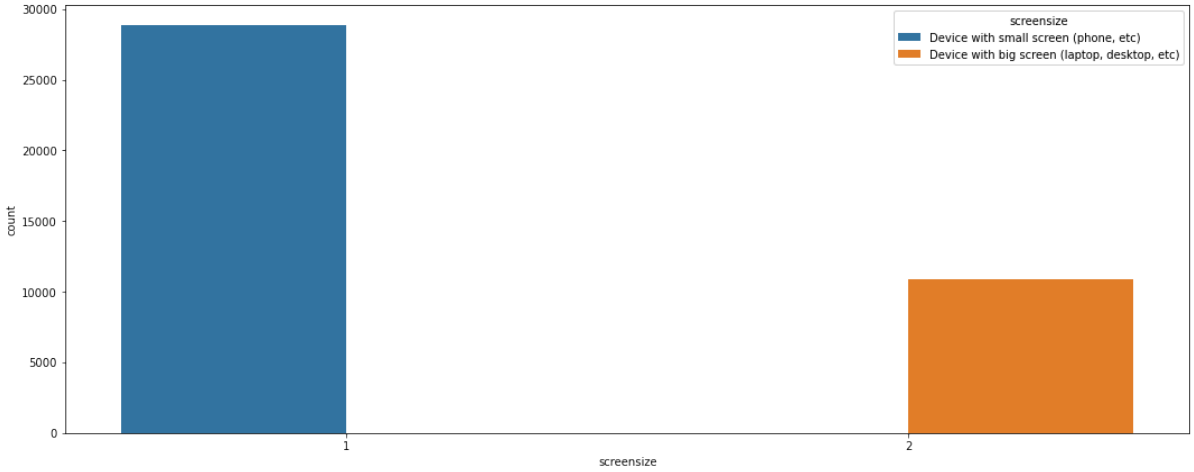


In [266]:
```
def makeScreensizeGroup(value):
    if value == 1:
        return 'Device with small screen (phone, etc)'
    if value == 2:
        return 'Device with big screen (laptop, desktop, etc)'
```

In [267]:
```
married = df['screensize'].apply(makeScreensizeGroup)
```

In [268]:
```
plt.figure(figsize=(18, 7))
sns.countplot(x=df['screensize'], hue=married)
```

Out[268]: <AxesSubplot:xlabel='screensize', ylabel='count'>



in Uniquenetworklocation Column

In [269]:
```
df.columns.get_loc('uniquenetworklocation')
```

Out[269]: 76

In [270]:
```
df['uniquenetworklocation'].unique()
```

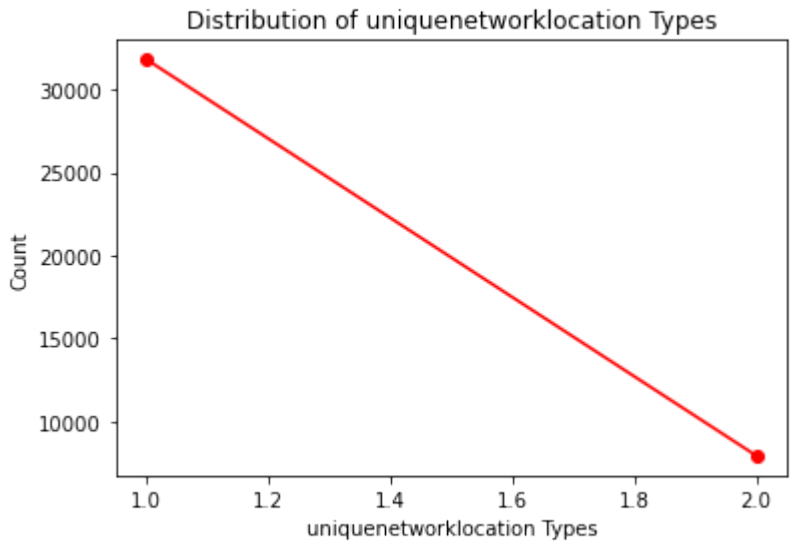
Out[270]: array([1, 2], dtype=int64)

In [271]:
```
df['uniquenetworklocation'].value_counts()
```

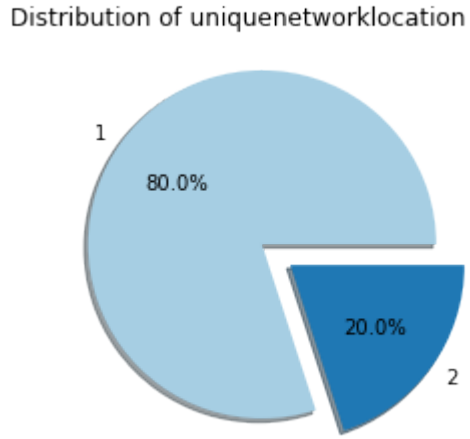
Out[271]:
```
1    31799
2     7951
Name: uniquenetworklocation, dtype: int64
```

In [272]:
```
value_counts = df['uniquenetworklocation'].value_counts().sort_index()
```

In [273]:
```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('uniquenetworklocation Types')
plt.ylabel('Count')
plt.title('Distribution of uniquenetworklocation Types')
plt.show()
```



In [274]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of uniquenetworklocation Types')
plt.show()
```



In [275]:
```
nan_values = df['uniquenetworklocation'].isnull().sum()
print(f"Number of NaN values in the 'country' column: {nan_values}")
```

```
Number of NaN values in the 'country' column: 0
```

In [276]:
```
columns_to_check = df.columns[76:77]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       uniquenetworklocation
0                      False
1                      False
2                      False
3                      False
4                      False
...                      ...
39770                  False
39771                  False
39772                  False
39773                  False
39774                  False

[39750 rows x 1 columns]
```

In [277]:
```
def makeUniquenetworklocationGroup(value):
    if value == 1:
        return 'Only one survey from the user\'s specific network in the da
    if value == 2:
        return 'Multiple surveys submitted from the network of this user'
```

In [278]:
```
uniquenetworklocation = df['uniquenetworklocation'].apply(makeUniquenetwor
```

In [279]:
```
plt.figure(figsize=(18, 7))
sns.countplot(x=df['uniquenetworklocation'], hue=uniquenetworklocation)
```

Out[279]: <AxesSubplot:xlabel='uniquenetworklocation', ylabel='count'>

in Source Column

In [280]:
```
df.columns.get_loc('source')
```

Out[280]: 43

In [281]:
```
df['source'].unique()
```

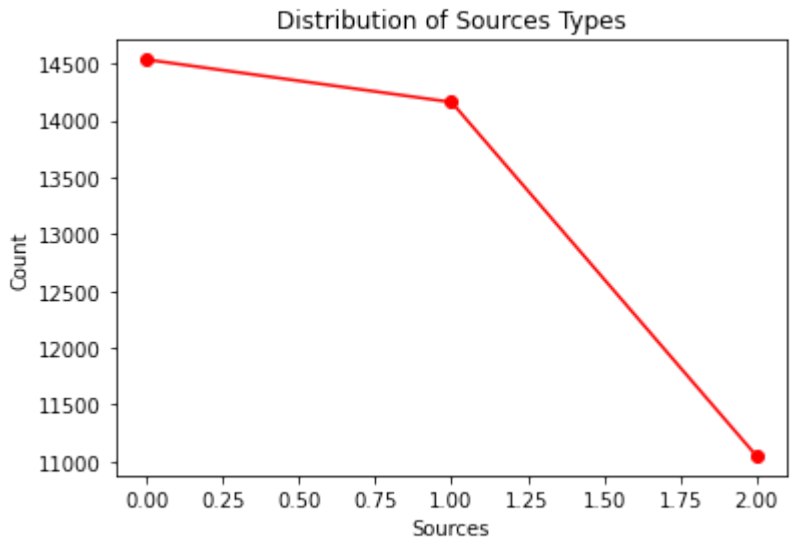
Out[281]: array([2, 0, 1], dtype=int64)

In [282]:
```
df['source'].value_counts()
```

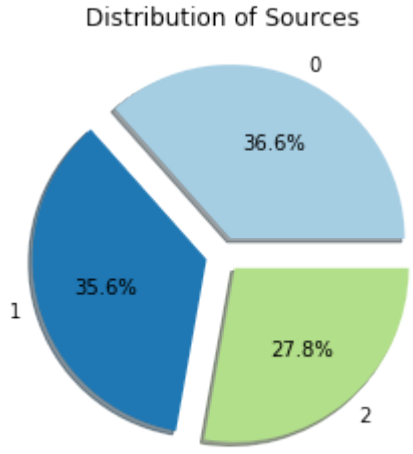
Out[282]:
```
0    14536
1    14162
2    11052
Name: source, dtype: int64
```

In [283]:
```
value_counts = df['source'].value_counts().sort_index()
```

In [284]:
```
plt.plot(value_counts.index, value_counts.values, color='r', marker='o')
plt.xlabel('Sources')
plt.ylabel('Count')
plt.title('Distribution of Sources Types')
plt.show()
```



In [285]:
```
explode_values = [0.1] * len(value_counts)
plt.pie(value_counts, labels=value_counts.index, explode=explode_values, a
plt.title('Distribution of Sources')
plt.show()
```

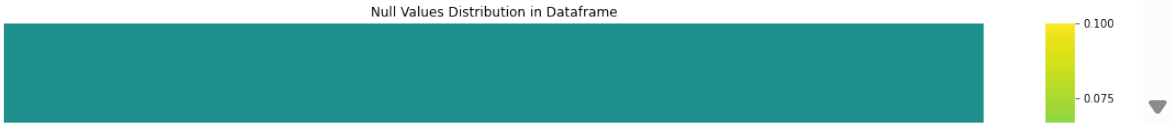


In [286]:
```
nan_values = df['uniquenetworklocation'].isnull().sum()
print(f"Number of NaN values in the 'country' column: {nan_values}")
```

```
Number of NaN values in the 'country' column: 0
```

In [287]:
```
columns_to_check = df.columns[43:44]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       source
0       False
1       False
2       False
3       False
4       False
...       ...
39770   False
39771   False
39772   False
39773   False
39774   False

[39750 rows x 1 columns]
```

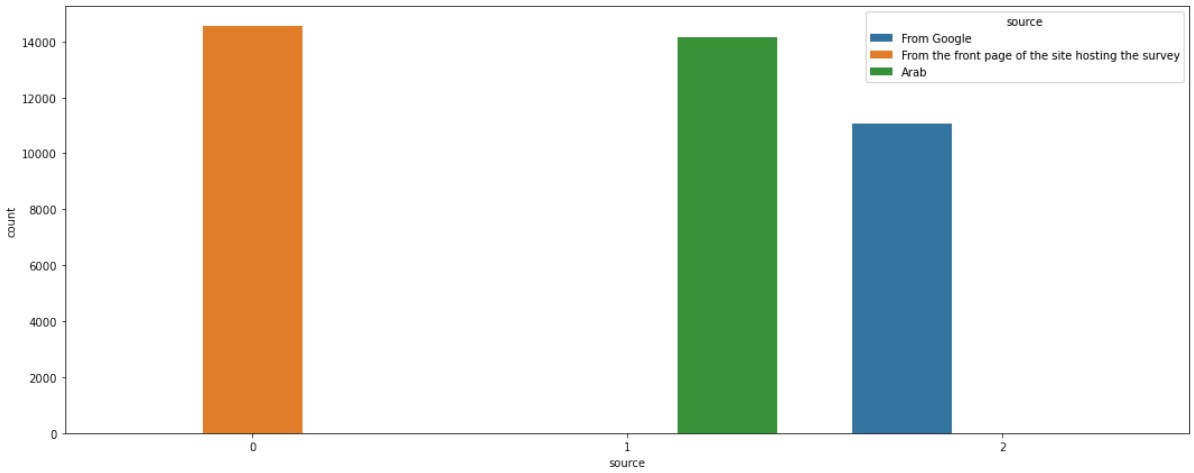


In [288]:
```
def makeSourceGroup(value):
    if value == 0:
        return 'From the front page of the site hosting the survey'
    if value == 1:
        return 'Arab'
    if value == 2:
        return 'From Google'
```

In [289]:
```
source = df['source'].apply(makeSourceGroup)
```

In [290]:
```
plt.figure(figsize=(18, 7))
sns.countplot(x=df['source'], hue=source)
```

Out[290]:
```
<AxesSubplot:xlabel='source', ylabel='count'>
```



in Major Column

In [291]:
```
1 df.columns.get_loc('major')
```

Out[291]:
```
84
```

In [292]:
```
1 df['major'].unique()
```

Out[292]:
```
array([nan, 'biology', 'Psychology', ...,
       '&#22810;&#23186;&#39636;&#35373;&#35336;',
       'public relation or administrations', 'computer sciece'],
      dtype=object)
```

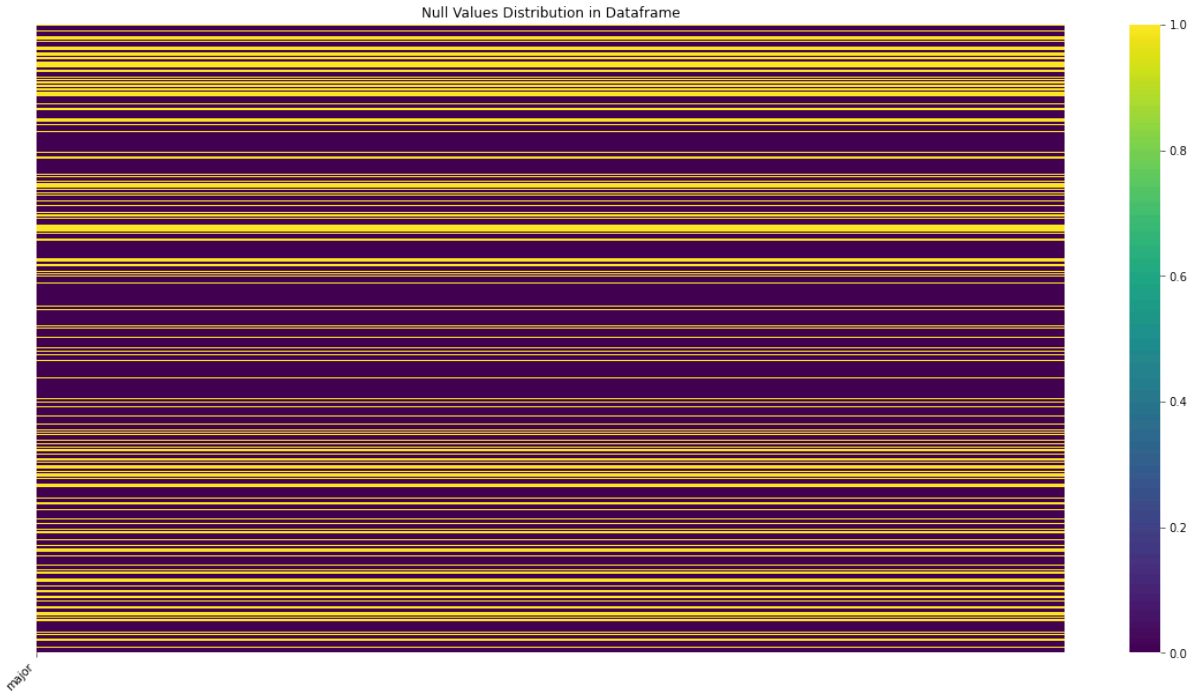
In [293]:
```
1 df['major'].value_counts()
```

Out[293]:
```
English                  1025
Psychology                850
Business                  620
Accounting                606
Engineering               582
                         ...
Mathematics & English       1
Comp Science                1
Art and Education           1
Veterinary science          1
computer sciece             1
Name: major, Length: 5308, dtype: int64
```

In [294]:
```
1 value_counts = df['major'].value_counts().sort_index()
```

In [295]:
```
columns_to_check = df.columns[84:85]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       major
0       True
1       True
2       True
3      False
4      False
...      ...
39770   True
39771  False
39772  False
39773  False
39774  False

[39750 rows x 1 columns]
```



In [296]:
```
nan_values = df['major'].isnull().sum()
print(f"Number of NaN values in the 'major' column: {nan_values}")
```

```
Number of NaN values in the 'major' column: 11399
```

In [297]:

```
def condition(title):
    if 'busin' in str(title).lower() or 'manage' in str(title).lower() or
        return 'Business/Management'
    elif 'information technology' in str(title).lower() or 'IT' in str(tit
        return 'I.T'
    elif 'math' in str(title).lower() or 'LOGISTICS' in str(title) or 'st'
        return 'Mathematics'
    elif 'computer' in str(title).lower():
        return 'I.T'
    elif 'bio' in str(title).lower() or 'Plant' in str(title) or 'plant' i
        return 'Biology'
    elif 'tesl' in str(title).lower() or 'TES' in str(title) or 'Teso' in
        return 'English'
    elif 'account' in str(title).lower() or 'Accoun' in str(title) or 'Acc
        return 'Accountacy'
    elif 'CA' in str(title):
        return 'CA'
    elif 'none' in str(title).lower() or '0' in str(title) or  '_' in str(
        return 'No Degree'
    elif 'nurs' in str(title).lower() or 'BSN' in str(title):
        return 'Nursing'
    elif '-' in str(title).lower() or 'NIL' in str(title):
        return 'No Degree'
    elif 'teach' in str(title).lower() or 'Lect' in str(title) or 'eet' in
        return 'Teaching'
    elif 'pharma' in str(title).lower() or 'medic' in str(title).lower() o
        return 'Pharmacy/Medical'
    elif 'doctor' in str(title).lower() or  'MBBS' in str(title) or 'Mbbs'
        return 'Doctor'
    elif 'no' in str(title).lower() or 'Undec' in str(title) or 'Idk' in s
        return 'No Degree'
    elif 'film' in str(title).lower() or 'Cinema' in str(title) or 'fil' i
        return 'Media'
    elif 'international' in str(title).lower() or 'Internatianal' in str(t
        return 'International Relations'
    elif 'human' in str(title).lower() or 'hr' in str(title).lower() or 'H
        return 'Human Resources'
    elif 'art' in str(title).lower() or 'Painting' in str(title) or 'Drawi
        return 'Arts'
    elif 'islam' in str(title).lower() or 'Muamalat' in str(title) or 'Qur
        return 'Islamic Studies'
    elif 'physio' in str(title).lower() or 'fis' in str(title).lower():
        return 'Physiotherapy'
    elif 'socio' in str(title).lower() or 'social' in str(title).lower() o
        return 'Sociology'
    elif 'bank' in str(title).lower():
        return 'Banking'
    elif 'agri' in str(title).lower():
        return 'Agriculture'
    elif 'Market' in str(title) or 'Finan' in str(title) or 'finance' in s
        return 'Marketing/Finance'
    elif 'counsel' in str(title).lower() or 'cauns' in str(title) or 'Kaun
        return 'Counselling'
    elif 'programming' in str(title).lower() or 'coding' in str(title).low
        return 'I.T'
    elif 'civil' in str(title).lower() or 'comp' in str(title).lower() or
        return 'Engineering'
```

```
    elif 'ict' in str(title).lower() or 'developer' in str(title).lower()
        return 'I.T'
    elif 'commu' in str(title).lower() or 'comm' in str(title).lower() or
        return 'Communications'
    elif 'administration' in str(title).lower() or 'admin' in str(title).l
        return 'Administration'
    elif 'psycho' in str(title).lower() or 'psy' in str(title).lower() or
        return 'Psychology'
    elif 'english' in str(title).lower() or 'Elglish' in str(title) or 'es
        return 'English'
    elif 'law' in str(title).lower() or 'BBA' in str(title) or 'llb' in st
        return 'Law'
    elif 'engineering' in str(title).lower() or 'engi' in str(title).lower
        return 'Engineering'
    elif 'architecture' in str(title).lower() or 'aechitecture' in str(tit
        return 'Architecture'
    elif 'design' in str(title).lower() or 'Desig' in str(title) or 'Dssig
        return 'Designer'
    elif 'science' in str(title).lower() or 'Sceince' in str(title) or 'Sc
        return 'Pure Sciences'
    elif 'physics' in str(title).lower() or 'Phsyics' in str(title) or 'EM
        return 'Physics'
    elif 'chemistry' in str(title).lower() or 'CIS' in str(title) or 'Chem
        return 'Chemistry'
    elif 'french' in str(title).lower() or 'Fr' in str(title):
        return 'French'
    elif 'religi' in str(title).lower() or 'Relegion' in str(title) or 'Re
        return 'Religious Studies'
    elif title=='&#1593;&#1604;&#1605; &#1606;&#1601;&#1587;' or title=='&
        return 'No Degree'
    elif 'Music' in str(title) or 'Dance' in str(title) or 'danc' in str(t
        return 'Music/Dance'
    elif 'pol' in str(title).lower() or 'Govern' in str(title) or 'Right'
        return 'Politics'
    elif 'photo' in str(title).lower() or 'Foto' in str(title) or 'Photo'
        return 'Photography'
    elif 'Television' in str(title) or 'telev' in str(title).lower():
        return 'Television'
    elif 'bahasa' in str(title).lower() or 'Bahasa' in str(title) or 'Mala
        return 'Malaysian languages'
    elif 'Urban' in str(title) or 'Town' in str(title) or 'town' in str(ti
        return 'Economic Developments'
    elif 'Public' in str(title) or 'public' in str(title).lower():
        return 'Public Relations'
    elif 'Writing' in str(title) or 'writing' in str(title).lower() or 'Sc
        return 'Writing/Author'
    elif 'philosophy' in str(title).lower() or 'Phil' in str(title) or 'ph
        return 'Philosophy'
    elif 'Actua' in str(title):
        return 'Acturial Studies'
    elif 'DENTALWORKS' in str(title) or 'dental' in str(title) or 'Dental'
        return 'Dentist'
    elif 'beaut' in str(title).lower() or 'Fashion' in str(title) or 'make
        return 'Fashion'
    elif 'Health' in str(title) or 'health' in str(title).lower() or 'well
        return 'Healthcare'
    elif 'Language' in str(title) or 'lang' in str(title).lower() or 'Laq'
```

```
        return 'Languages'
    elif 'cook' in str(title).lower() or 'bakery' in str(title).lower() or
        return 'Cookings'
    elif 'Hotel' in str(title) or 'hotel' in str(title).lower() or 'food s
        return 'Hotel Management'
    elif 'therapy' in str(title).lower() or 'ot' in str(title).lower() or
        return 'Therapeutical Studies'
    elif 'veter' in str(title).lower() or 'Veter' in str(title) or 'Vet' i
        return 'Veterinary'
    elif 'Survey' in str(title) or 'survey' in str(title) or 'serveyors' i
        return 'Surveyour Studies'
    elif 'Aircraft' in str(title) or 'aircraft' in str(title).lower() or '
        return 'Aircrafts'
    elif 'environment' in str(title).lower() or 'Environment' in str(title
        return 'Environmental Educations'
    elif 'Syariah' in str(title) or 'syariah' in str(title):
        return 'Syrian Languages'
    elif 'judicial' in str(title).lower() or 'juri' in str(title).lower()
        return 'Judicial Studies'
    elif 'Liter' in str(title) or 'literature' in str(title) or 'litt' in
        return 'Literature'
    elif 'child' in str(title).lower() or 'Child' in str(title) or 'Presch
        return 'Child Educations'
    elif 'Tour' in str(title) or 'tour'  in str(title).lower():
        return 'Tourisms'
    elif 'Gam' in str(title) or 'game' in str(title).lower():
        return 'Gaming'
    elif 'education' in str(title).lower() or 'Education' in str(title) or
        return 'B.Ed or M.Ed'
    elif 'Sport' in str(title) or 'sport' in str(title).lower():
        return 'Sports'
    elif 'Petro' in str(title):
        return 'Petroleum'
    elif 'Journ' in str(title) or 'jour' in str(title).lower() or 'Joun' i
        return 'Journalism'
    elif 'Mandarin' in str(title):
        return 'Chinese/Mandarin Languages'
    elif 'Electrician' in str(title):
        return 'Electrician'
    elif 'Network' in str(title) or 'network' in str(title).lower():
        return 'Networking'
    elif 'geo' in str(title).lower() or 'GEO' in str(title):
        return 'Geography'
    elif 'Librarian' in str(title) or 'lib' in str(title).lower():
        return 'Librarian'
    elif 'Mission' in str(title) or 'mission' in str(title).lower():
        return 'Missionary Studies'
    elif 'Forensic' in str(title) or 'foren' in str(title).lower() or 'Cri
        return 'Forensic/Criminal studies'
    elif 'Animation' in str(title) or 'animation' in str(title).lower() or
        return 'Animations'
    elif 'aqua' in str(title).lower() or 'Aqu' in str(title):
        return 'Aquaculture'
    elif 'soldier' in str(title).lower() or 'lwa' in str(title).lower() or
        return 'Army'
    elif 'Kinesi' in str(title) or 'kines' in str(title).lower() or 'hod'
        return 'Human Kinetics'
```

```
    elif 'Horti' in str(title) or 'horti' in str(title) or 'Landscape' in
        return 'Horticulture'
    elif 'commerce' in str(title).lower() or 'Coome' in str(title):
        return 'Commerce'
    elif 'Speech' in str(title) or 'speech' in str(title).lower():
        return 'Speech Pathology'
    elif 'SECRET' in str(title) or 'secret' in str(title).lower():
        return 'Secretary'
    elif 'Animals' in str(title) or 'animal' in str(title).lower() or 'Pet
        return 'Animal Care'
    elif 'Organisation' in str(title) or 'organi' in str(title).lower():
        return 'Organizational Behaviour'
    elif 'event' in str(title).lower() or 'Event' in str(title):
        return 'Event Managment'
    elif 'radiology' in str(title).lower() or 'Radiography' in str(title)
        return 'Radiography'
    elif 'nutrition' in str(title).lower() or 'Nutrition' in str(title):
        return 'Nutritionist'
    elif 'Audit' in str(title) or 'audit' in str(title).lower():
        return 'Auditing'
    elif 'Neuro' in str(title) or 'neuroligy' in str(title).lower():
        return 'Neurology'
    elif 'Anato' in str(title) or 'anat' in str(title).lower():
        return 'Anatomy'
    elif 'trade' in str(title).lower():
        return 'Trading'
    elif 'Interpre' in str(title) or 'translation' in str(title).lower():
        return 'Interpreter'
    elif 'audio' in str(title).lower() or 'Audio' in str(title):
        return 'Audiology'
    elif 'insurance' in str(title).lower() or 'Insurance' in str(title):
        return 'Insurances'
    elif 'archaeology' in str(title).lower() or 'archaeology' in str(title
        return 'Archeology'
    elif 'SERV'in str(title) or 'service' in str(title).lower():
        return 'Service Training'
    elif 'GERMAN' in str(title) or 'german' in str(title).lower():
        return 'German'
    elif 'KOREAN' in str(title) or 'Korea' in str(title):
        return 'Korean'
    elif 'valuat' in str(title).lower() or 'valuer' in str(title).lower():
        return 'Registered Valuer'
    elif 'skil' in str(title).lower() or 'Skill' in str(title) or 'Profess
        return 'Skilled Labour'
    elif 'virology' in str(title):
        return 'Virology'
    elif 'lab' in str(title).lower() or 'Lab' in str(title) or 'MLT' in st
        return 'Laboratory Worker'
    elif 'GENERAL' in str(title) or 'General' in str(title):
        return 'General'
    elif 'Opto' in str(title) or 'opto' in str(title).lower():
        return 'Optometry'
    elif 'Zoo' in str(title) or 'zoo' in str(title).lower():
        return 'Zoology'
    elif 'office' in str(title).lower() or 'Office' in str(title):
        return 'Office Skills'
    elif 'found' in str(title).lower() or 'Found' in str(title):
```

```
        return 'Foundation Education'
    elif 'general' in str(title).lower() or 'General' in str(title):
        return 'General Education'
    elif 'real estate' in str(title).lower() or 'property' in str(title).l
        return 'Realtor'
    elif 'Meteorology' in str(title) or 'Metrology' in str(title):
        return 'Meterology'
    elif 'operations' in str(title).lower() or 'Operation' in str(title):
        return 'Operational Managment'
    elif 'Merchandising' in str(title) or 'merchand' in str(title).lower()
        return 'Merchandising'
    elif 'Spanish' in str(title):
        return 'Spanish'
    elif 'Nature' in str(title) or 'natur' in str(title).lower():
        return 'Nature Conservation/Resources'
    elif title=='a level ' or title==' ':
        return 'No Degree'
    elif 'Corporate' in str(title) or 'corporate' in str(title).lower():
        return 'Corporate'
    elif 'greek' in str(title).lower() or 'Greek' in str(title):
        return 'Greek'
    elif 'Behaviour' in str(title) or 'Behavior' in str(title) or 'Organiz
        return 'Behaviour Analysis'
    elif 'publish' in str(title).lower():
        return 'Publishing'
    elif 'Safety' in str(title) or 'safety' in str(title).lower():
        return 'Safety Training'
    elif 'genetic' in str(title).lower() or 'Genetic' in str(title):
        return 'Genetics'
    elif 'Dietetic' in str(title):
        return 'Dietician'
    elif 'Production' in str(title) or 'manufacturing' in str(title).lower
        return 'Production And Manufacturing'
    elif 'Welding' in str(title):
        return 'Welding'
    elif 'Geron' in str(title):
        return 'Gerontology'
    elif 'Research' in str(title) or 'Ph D' in str(title):
        return 'Ph.D'
    elif 'arabic' in str(title).lower() or 'Arabic' in str(title):
        return 'Arabic'

    else:
        return title
```

In [298]:

```
df['major'] = df['major'].apply(condition)
```

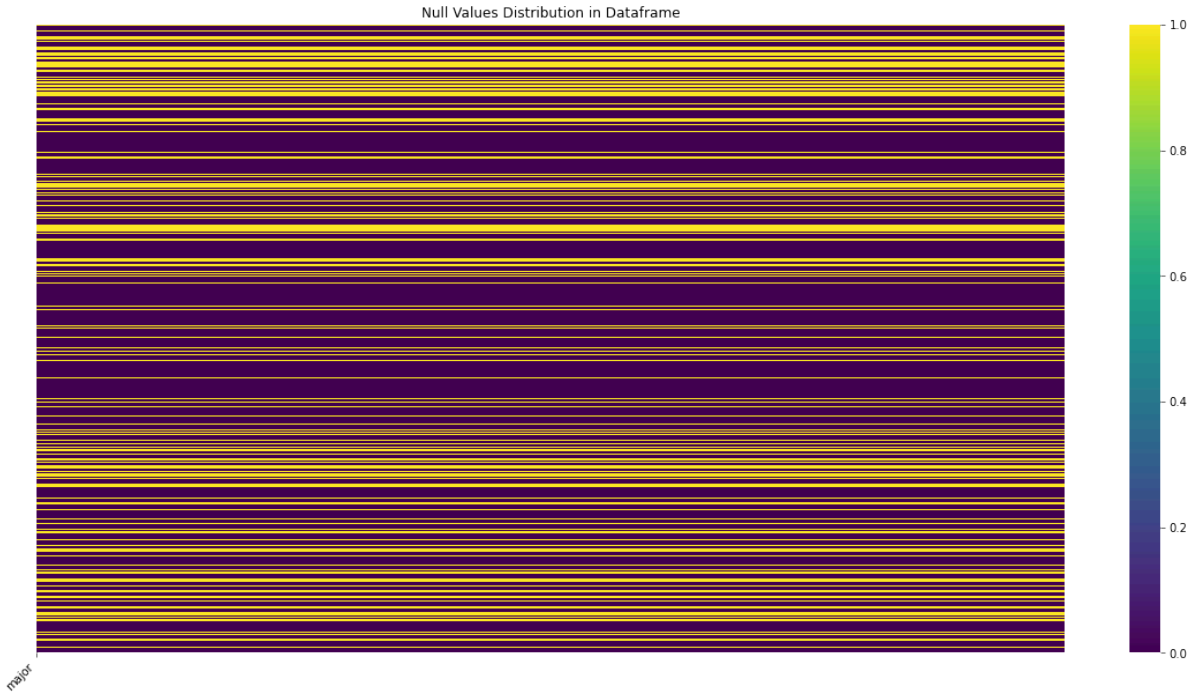
In [299]:

```
lis=[]
for x in df['major']:
    lis.append(x)
print(set(lis))
```

```
{nan, 'Pathology', 'Corrosion ', 'Doctor', 'Journalism', 'Information', 'Art
s', 'Geography', 'Builders', 'Mining ', 'Zoology', 'clinical measurement', 'R
eligious Studies', 'Animal Care', 'General', 'Languages', 'Veterinary', 'Anat
omy', 'Palaeontology', 'Insurances', 'Tourisms', 'Accountacy', 'Counselling',
'Supply chain', 'Meterology', 'Dutch', 'Child Educations', 'Kiin', 'General E
ducation', 'French', 'Aircrafts', 'Banking', 'Arabic', 'Registered Valuer',
'Politics', 'Marketing/Finance', 'Interpreter', 'Sociology', 'hvac', 'Merchan
dising', 'Media', 'Gerontology', 'Trading', 'Office Skills', 'Architecture',
'Missionary Studies', 'Malaysian languages', 'College diploma', 'Japanese',
'Cretive Visual', 'Writing/Author', 'Bachelor', 'Hotel Management', 'Spanis
h', 'Youth Work', 'Law', 'Foundation Education', 'Chargeman', 'Russian philol
ogy', 'Army', 'Organizational Behaviour', 'Bookkeeping ', 'Sports', 'Internat
ional Relations', 'Business/Management', 'Photography', 'theology', 'Leadersh
ip', 'Optometry', 'Animations', 'Healthcare', 'Museology', 'usa', 'Product De
velopment', 'Aquaculture', 'Human Resources', 'Service Training', 'Psycholog
y', 'Information ', 'German', 'Corporate', 'Radiography', 'Danish', 'Skilled
Labour', 'Laboratory Worker', 'B.Ed or M.Ed', 'Music/Dance', 'Economic Develo
pments', 'Ophthmalology', 'Physics', 'Physiotherapy', 'Afrikaans', 'Korean',
'Nature Conservation/Resources', 'Publishing', 'Behaviour Analysis', 'Environ
mental Educations', 'Networking', 'Commerce', 'Gis', 'English', 'Philosophy',
'Operational Managment', 'Ph.D', 'Forensic/Criminal studies', 'Islamic Studie
s', 'Sculpture', 'Chinese', 'CA', 'Neurology', 'Designer', 'Therapeutical Stu
dies', 'Librarian', 'Human Kinetics', 'Gaming', 'Realtor', 'Virology', 'Surve
your Studies', 'Crisis intervention', 'Dentist', 'Cookings', 'Singer', 'Petro
leum', 'epidemiology', 'Fashion', 'Pure Sciences', 'Genetics', 'Welding', 'I.
T', 'harvard', 'Audiology', 'maintenance', 'midwivery', 'No Degree', 'Teachin
g', 'Agriculture', 'Safety Training', 'Judicial Studies', 'Dietician', 'Gree
k', 'Pharmacy/Medical', 'Administration', 'Horticulture', 'Syrian Languages',
'Biology', 'Event Managment', 'Cabin Crew', 'Mathematics', 'Wildlife resource
s', 'Communications', 'Production And Manufacturing', 'Couselling', 'Engineer
ing', 'Archeology', 'portuguese', 'Nursing', 'Public Relations', 'Chemistry',
'IR'}
```

In [300]:
```
columns_to_check = df.columns[84:85]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       major
0       True
1       True
2       True
3      False
4      False
...      ...
39770   True
39771  False
39772  False
39773  False
39774  False

[39750 rows x 1 columns]
```



In [301]:
```
nan_values = df['major'].isnull().sum()
print(f"Number of NaN values in the 'major' column: {nan_values}")
```

```
Number of NaN values in the 'major' column: 11399
```

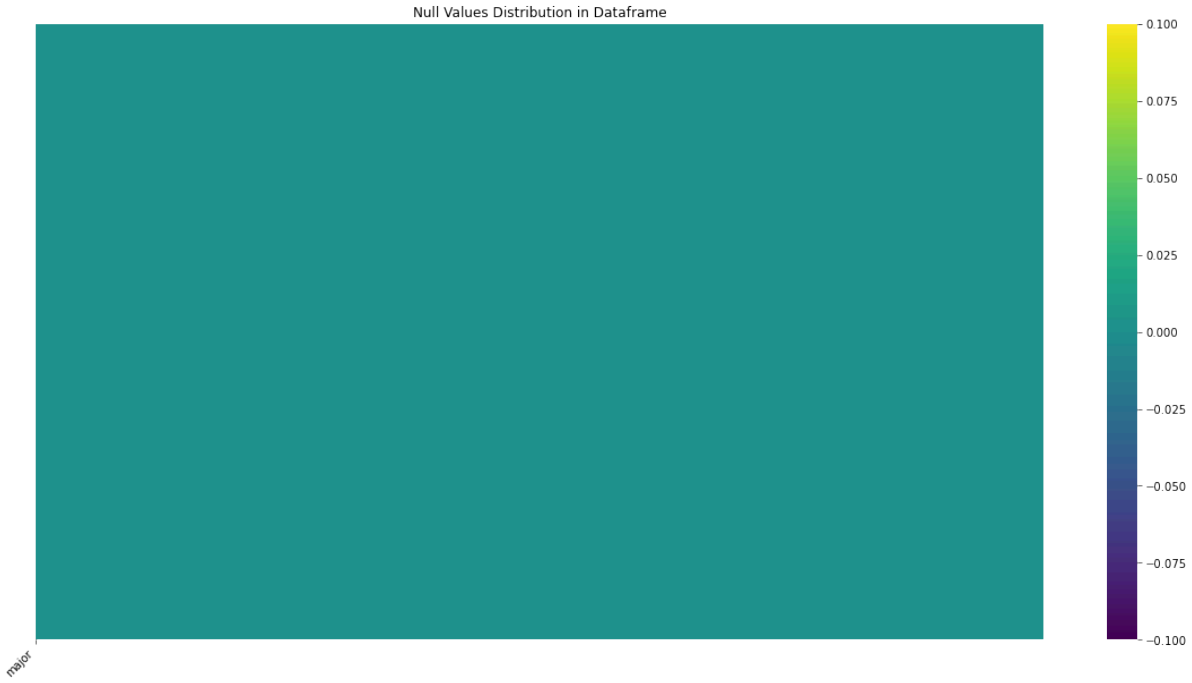
In [302]:
```
df['major'].value_counts()
```

Out[302]:
```
Engineering            3902
Business/Management    3217
I.T                    2570
Mathematics            2362
Psychology             1945
                       ...
Mining                    1
usa                       1
Ophthmalology             1
Cabin Crew                1
Virology                  1
Name: major, Length: 158, dtype: int64
```

In [303]:
```
df=df.replace([np.inf, -np.inf], np.nan)
df=df.dropna()
```

In [304]:
```
columns_to_check = df.columns[84:85]
plot_null_values(df, columns_to_check)
```

```
Null values in the specified columns:
       major
3      False
4      False
6      False
7      False
8      False
...      ...
39768  False
39771  False
39772  False
39773  False
39774  False

[28351 rows x 1 columns]
```



In [305]:
```
nan_values = df['major'].isnull().sum()
print(f"Number of NaN values in the 'major' column: {nan_values}")
```

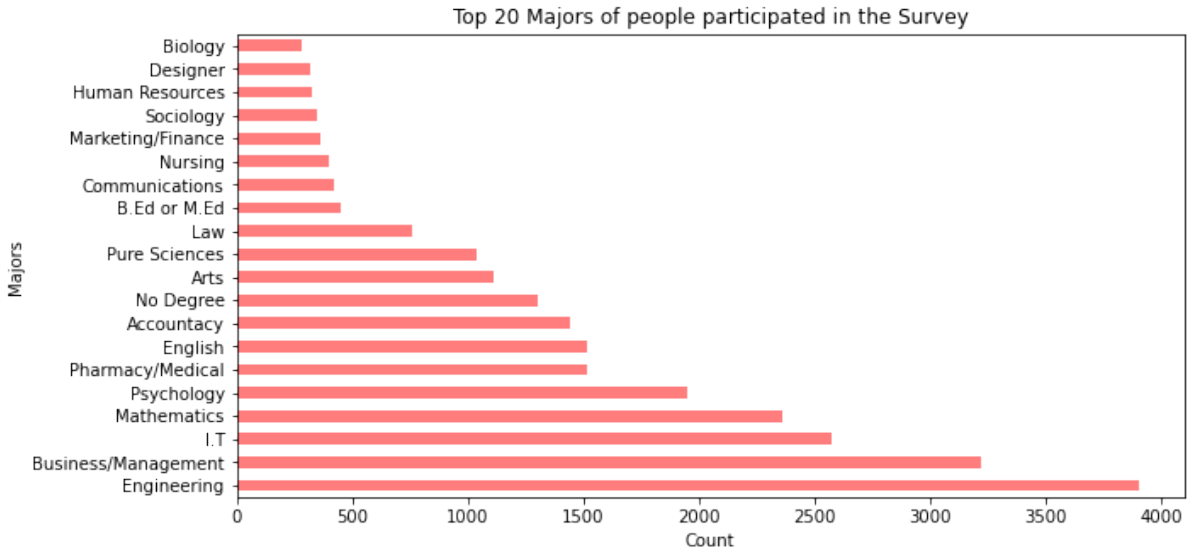
```
Number of NaN values in the 'major' column: 0
```

In [306]:
```
df.shape
```

Out[306]:
```
(28351, 86)
```

In [307]:
```
plt.figure(figsize=(10,5))
df['major'].value_counts()[:20].plot(kind='barh',color='r', alpha=0.5)
plt.ylabel('Majors')
plt.xlabel('Count')
plt.title('Top 20 Majors of people participated in the Survey')
```

Out[307]: Text(0.5, 1.0, 'Top 20 Majors of people participated in the Survey')



In [308]:
```
duplicate_rows = df.duplicated()
print("Duplicate Rows except first occurrence:")
duplicate_rows
```

```
Duplicate Rows except first occurrence:
```

Out[308]:
```
3        False
4        False
6        False
7        False
8        False
         ...
39768    False
39771    False
39772    False
39773    False
39774    False
Length: 28351, dtype: bool
```

In [309]:
```
1 df
```

Out[309]:

	Q1A	Q2A	Q3A	Q4A	Q5A	Q6A	Q7A	Q8A	Q9A	Q10A	Q11A	Q12A	Q13A	Q14A	Q
3	2	3	2	1	3	3	4	2	3	3	2	1	1	4	
4	2	2	3	4	4	2	4	4	4	3	2	4	4	4	
6	1	1	2	3	4	1	3	3	3	4	1	2	2	2	
7	1	1	1	1	3	2	2	1	1	1	2	1	1	2	
8	4	4	3	4	3	4	4	4	4	3	4	4	4	3	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
39768	2	1	1	1	2	2	1	2	1	1	2	2	2	2	
39771	3	4	3	4	3	4	4	4	3	4	4	4	4	4	
39772	2	1	2	1	1	1	1	1	2	1	1	1	2	1	
39773	3	1	2	2	3	3	3	4	3	1	3	3	4	4	
39774	2	1	2	1	4	2	1	1	1	1	3	1	3	1	

28351 rows × 86 columns

In [310]:
```
1 df = df.reset_index(drop=True)
```

In [311]:
```
1 df
```

Out[311]:

	Q1A	Q2A	Q3A	Q4A	Q5A	Q6A	Q7A	Q8A	Q9A	Q10A	Q11A	Q12A	Q13A	Q14A	Q
0	2	3	2	1	3	3	4	2	3	3	2	1	1	4	
1	2	2	3	4	4	2	4	4	4	3	2	4	4	4	
2	1	1	2	3	4	1	3	3	3	4	1	2	2	2	
3	1	1	1	1	3	2	2	1	1	1	2	1	1	2	
4	4	4	3	4	3	4	4	4	4	3	4	4	4	3	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
28346	2	1	1	1	2	2	1	2	1	1	2	2	2	2	
28347	3	4	3	4	3	4	4	4	3	4	4	4	4	4	
28348	2	1	2	1	1	1	1	1	2	1	1	1	2	1	
28349	3	1	2	2	3	3	3	4	3	1	3	3	4	4	
28350	2	1	2	1	4	2	1	1	1	1	3	1	3	1	

28351 rows × 86 columns

(4) Machine Learning

In [312]:
```
dass = df.copy()
```

In [313]:
```
dass_part2=df.iloc[:,42:]
dass_part2
```

Out[313]:

	country	source	TIPI1	TIPI2	TIPI3	TIPI4	TIPI5	TIPI6	TIPI7	TIPI8	TIPI9	TIPI10	VCL1
0	US	2	1	1	7	4	6	4	6	1	6	1	1
1	MY	2	2	5	3	6	5	5	5	6	3	3	1
2	MX	2	2	5	6	5	3	2	6	3	5	5	1
3	GB	2	7	6	4	5	3	2	6	3	5	2	1
4	US	0	1	4	5	7	5	7	6	7	1	4	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
28346	US	0	6	5	6	7	6	4	6	5	5	3	1
28347	MY	1	4	5	5	7	4	6	4	7	4	4	1
28348	US	0	6	6	7	5	6	3	6	1	5	4	0
28349	US	2	1	6	5	7	3	5	3	5	3	4	1
28350	MY	1	6	2	3	5	6	3	5	5	1	2	1

28351 rows × 44 columns

In [314]:
```
Qs=dass.filter(regex='Q\d{1,2}A')
Qs
```

Out[314]:

	Q1A	Q2A	Q3A	Q4A	Q5A	Q6A	Q7A	Q8A	Q9A	Q10A	Q11A	Q12A	Q13A	Q14A
0	2	3	2	1	3	3	4	2	3	3	2	1	1	4
1	2	2	3	4	4	2	4	4	4	3	2	4	4	4
2	1	1	2	3	4	1	3	3	3	4	1	2	2	2
3	1	1	1	1	3	2	2	1	1	1	2	1	1	2
4	4	4	3	4	3	4	4	4	4	3	4	4	4	3
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
28346	2	1	1	1	2	2	1	2	1	1	2	2	2	2
28347	3	4	3	4	3	4	4	4	3	4	4	4	4	4
28348	2	1	2	1	1	1	1	1	2	1	1	1	2	1
28349	3	1	2	2	3	3	3	4	3	1	3	3	4	4
28350	2	1	2	1	4	2	1	1	1	1	3	1	3	1

See This Photo for How This Looked 😳 !!!

0 Did not apply to me at all

1 Applied to me to some degree, or some of the time

2 Applied to me to a considerable degree, or a good part of time

3 Applied to me very much, or most of the time

In [315]:
```
def sub(Qs):
    return Qs.subtract(1,axis=1)
```

In [316]:
```
Qs = sub(Qs)
```

In [317]:
```
Qs
```

Out[317]:

	Q1A	Q2A	Q3A	Q4A	Q5A	Q6A	Q7A	Q8A	Q9A	Q10A	Q11A	Q12A	Q13A	Q14A	Q
0	1	2	1	0	2	2	3	1	2	2	1	0	0	3	
1	1	1	2	3	3	1	3	3	3	2	1	3	3	3	
2	0	0	1	2	3	0	2	2	2	3	0	1	1	1	
3	0	0	0	0	2	1	1	0	0	0	1	0	0	1	
4	3	3	2	3	2	3	3	3	3	2	3	3	3	2	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
28346	1	0	0	0	1	1	0	1	0	0	1	1	1	1	
28347	2	3	2	3	2	3	3	3	2	3	3	3	3	3	
28348	1	0	1	0	0	0	0	0	1	0	0	0	1	0	
28349	2	0	1	1	2	2	2	3	2	0	2	2	3	3	
28350	1	0	1	0	3	1	0	0	0	0	2	0	2	0	

28351 rows × 42 columns

1. S	2. A	3. D	4. A
5. D	6. S	7. A	8. S
9. A	10. D	11. S	12. S
13. D	14. S	15. A	16. D
17. D	18. S	19. A	20. A
21. D	22. S	23. A	24. D
25. A	26. D	27. S	28. A
29. S	30. A	31. D	32. S
33. S	34. D	35. S	36. A
37. D	38. D	39. S	40. A
41. A	42. D		

Scores of Depression, Anxiety and Stress are calculated by summing the scores for the relevant items.
The depression scale items are 3, 5, 10, 13, 16, 17, 21, 24, 26, 31, 34, 37, 38, 42.
The anxiety scale items are 2, 4, 7, 9, 15, 19, 20, 23, 25, 28, 30, 36, 40, 41.
The stress scale items are 1, 6, 8, 11, 12, 14, 18, 22, 27, 29, 32, 33, 35, 39.

	Depression	Anxiety	Stress
Normal	0-9	0-7	0-14
Mild	10-13	8-9	15-18
Moderate	14-20	10-14	19-25
Severe	21-27	15-19	26-33
Extremely Severe	28+	20+	34+

In [318]:
```
DASS_keys = {'Depression': [3, 5, 10, 13, 16, 17, 21, 24, 26, 31, 34, 37,
             'Anxiety': [2, 4, 7, 9, 15, 19, 20, 23, 25, 28, 30, 36, 40, 4
             'Stress': [1, 6, 8, 11, 12, 14, 18, 22, 27, 29, 32, 33, 35, 3
```

In [319]:
```
depression = []
anxiety = []
stress = []
```

In [320]:
```
for i in DASS_keys["Depression"]:
    depression.append('Q'+str(i)+'A')
```

In [321]:
```
for i in DASS_keys["Anxiety"]:
    anxiety.append('Q'+str(i)+'A')
```

In [322]:
```
for i in DASS_keys["Stress"]:
    stress.append('Q'+str(i)+'A')
```

In [323]:
```
print(depression)
print(anxiety)
print(stress)
```

```
['Q3A', 'Q5A', 'Q10A', 'Q13A', 'Q16A', 'Q17A', 'Q21A', 'Q24A', 'Q26A', 'Q31
A', 'Q34A', 'Q37A', 'Q38A', 'Q42A']
['Q2A', 'Q4A', 'Q7A', 'Q9A', 'Q15A', 'Q19A', 'Q20A', 'Q23A', 'Q25A', 'Q28A',
'Q30A', 'Q36A', 'Q40A', 'Q41A']
['Q1A', 'Q6A', 'Q8A', 'Q11A', 'Q12A', 'Q14A', 'Q18A', 'Q22A', 'Q27A', 'Q29A',
'Q32A', 'Q33A', 'Q35A', 'Q39A']
```

In [324]:
```
depression= Qs.filter(depression)
anxiety = Qs.filter(anxiety)
stress = Qs.filter(stress)
```

In [325]:
```
depression
```

Out[325]:

	Q3A	Q5A	Q10A	Q13A	Q16A	Q17A	Q21A	Q24A	Q26A	Q31A	Q34A	Q37A	Q38A	Q
0	1	2	2	0	1	2	0	0	1	2	3	1	0	
1	2	3	2	3	2	3	2	1	3	2	3	2	2	
2	1	3	3	1	3	1	3	2	1	3	2	3	3	
3	0	2	0	0	0	0	0	0	1	0	0	0	0	
4	2	2	2	3	3	2	2	2	3	3	3	3	2	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
28346	0	1	0	1	1	0	0	1	1	0	0	0	0	
28347	2	2	3	3	3	2	3	3	3	3	3	2	3	
28348	1	0	0	1	0	0	0	1	0	1	0	0	0	
28349	1	2	0	3	0	1	1	1	2	1	1	0	1	
28350	1	3	0	2	3	3	3	1	1	1	2	1	3	

28351 rows × 14 columns

In [326]:
```
anxiety
```

Out[326]:

	Q2A	Q4A	Q7A	Q9A	Q15A	Q19A	Q20A	Q23A	Q25A	Q28A	Q30A	Q36A	Q40A	Q4
0	2	0	3	2	1	0	1	0	0	0	2	0	3	
1	1	3	3	3	3	3	3	3	3	3	3	3	3	
2	0	2	2	2	2	0	2	2	1	1	2	1	1	
3	0	0	1	0	1	0	1	0	1	0	0	0	0	
4	3	3	3	3	3	3	3	3	1	3	2	3	3	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
28346	0	0	0	0	0	1	0	0	0	0	1	0	0	
28347	3	3	3	2	3	3	3	2	2	2	2	2	2	
28348	0	0	0	1	0	0	0	0	0	0	0	0	0	
28349	0	1	2	2	0	0	1	0	0	2	0	1	1	
28350	0	0	0	0	0	3	2	0	1	1	0	1	2	

28351 rows × 14 columns

In [327]:
```
1 stress
```

Out[327]:

	Q1A	Q6A	Q8A	Q11A	Q12A	Q14A	Q18A	Q22A	Q27A	Q29A	Q32A	Q33A	Q35A	Q3
0	1	2	1	1	0	3	0	0	3	2	0	1	0	
1	1	1	3	1	3	3	3	2	1	1	3	3	2	
2	0	0	2	0	1	1	1	0	0	1	1	3	1	
3	0	1	0	1	0	1	1	0	1	0	0	0	0	
4	3	3	3	3	3	2	3	3	1	3	1	3	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
28346	1	1	1	1	1	1	1	1	1	1	1	1	1	
28347	2	3	3	3	3	3	2	3	2	2	2	2	2	
28348	1	0	0	0	0	0	0	0	1	1	0	1	0	
28349	2	2	3	2	2	3	2	3	3	2	2	3	2	
28350	1	1	0	2	0	0	2	1	2	2	1	1	1	

28351 rows × 14 columns

In [328]:
```
1 def scores(source):
2     col=list(source)
3     source['Total_Count']=source[col].sum(axis=1)
4     return source
```

In [329]:
```
1 depression=scores(depression)
2 anxiety=scores(anxiety)
3 stress=scores(stress)
```

In [330]:
```
1 depression.head()
```

Out[330]:

	Q3A	Q5A	Q10A	Q13A	Q16A	Q17A	Q21A	Q24A	Q26A	Q31A	Q34A	Q37A	Q38A	Q42A
0	1	2	2	0	1	2	0	0	1	2	3	1	0	1
1	2	3	2	3	2	3	2	1	3	2	3	2	2	2
2	1	3	3	1	3	1	3	2	1	3	2	3	3	2
3	0	2	0	0	0	0	0	0	1	0	0	0	0	1
4	2	2	2	3	3	2	2	2	3	3	3	3	2	3

In [331]:
```
1 anxiety.head()
```

Out[331]:

	Q2A	Q4A	Q7A	Q9A	Q15A	Q19A	Q20A	Q23A	Q25A	Q28A	Q30A	Q36A	Q40A	Q41A
0	2	0	3	2	1	0	1	0	0	0	2	0	3	3
1	1	3	3	3	3	3	3	3	3	3	3	3	3	3
2	0	2	2	2	2	0	2	2	1	1	2	1	1	1
3	0	0	1	0	1	0	1	0	1	0	0	0	0	0
4	3	3	3	3	3	3	3	3	1	3	2	3	3	3

In [332]:
```
1 stress.head()
```

Out[332]:

	Q1A	Q6A	Q8A	Q11A	Q12A	Q14A	Q18A	Q22A	Q27A	Q29A	Q32A	Q33A	Q35A	Q39A
0	1	2	1	1	0	3	0	0	3	2	0	1	0	2
1	1	1	3	1	3	3	3	2	1	1	3	3	2	2
2	0	0	2	0	1	1	1	0	0	1	1	3	1	3
3	0	1	0	1	0	1	1	0	1	0	0	0	0	1
4	3	3	3	3	3	2	3	3	1	3	1	3	1	1

in Depression Set

In [333]:
```
1 Depression=pd.merge(depression,dass_part2,how='left',left_index=True,right
2 Depression.head()
```

Out[333]:

	Q3A	Q5A	Q10A	Q13A	Q16A	Q17A	Q21A	Q24A	Q26A	Q31A	Q34A	Q37A	Q38A	Q42A
0	1	2	2	0	1	2	0	0	1	2	3	1	0	1
1	2	3	2	3	2	3	2	1	3	2	3	2	2	2
2	1	3	3	1	3	1	3	2	1	3	2	3	3	2
3	0	2	0	0	0	0	0	0	1	0	0	0	0	1
4	2	2	2	3	3	2	2	2	3	3	3	3	2	3

In [334]:

```
def predict_depression(x):
    if x<=9:
        return 'Normal'
    if  10<=x<=13:
        return 'Mild'
    if 14<=x<=20:
        return 'Moderate'
    if 21<=x<=27:
        return 'Severe'
    if x>28:
        return 'Extremely Severe'
```

In [335]:

```
Depression['predict']=Depression['Total_Count'].apply(predict_depression)
```

In [336]:

```
Depression
```

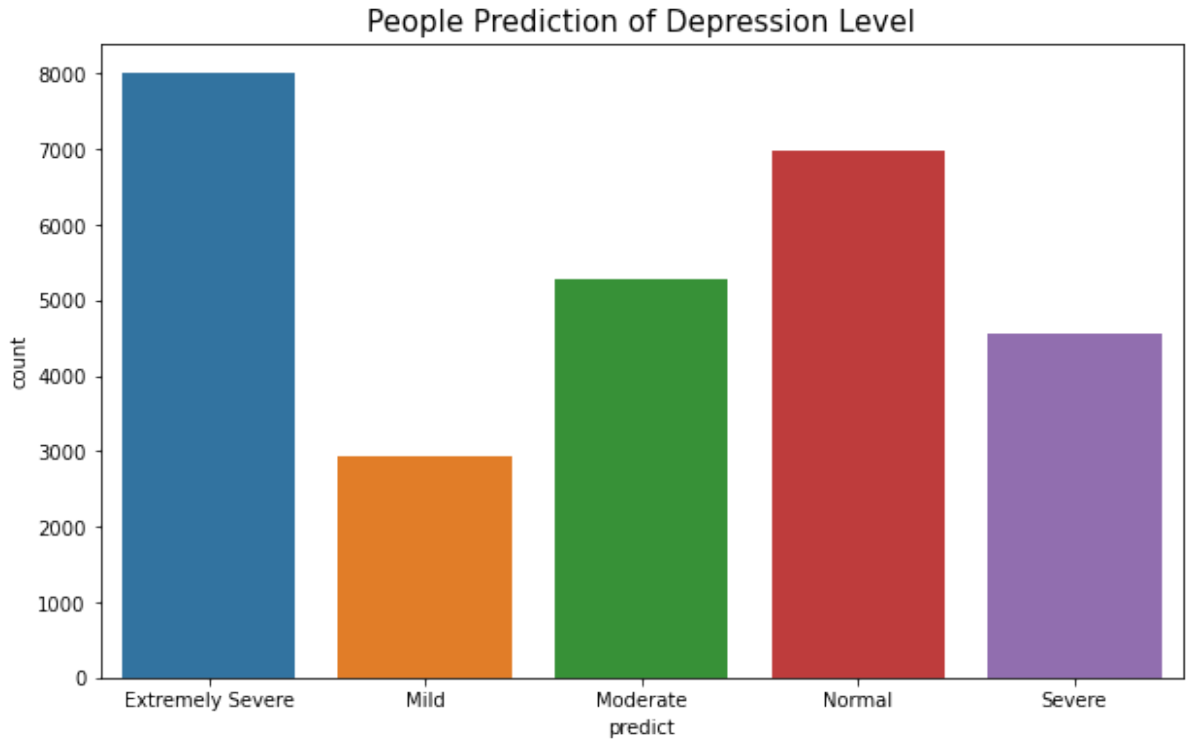
Out[336]:

	Q3A	Q5A	Q10A	Q13A	Q16A	Q17A	Q21A	Q24A	Q26A	Q31A	Q34A	Q37A	Q38A	C
0	1	2	2	0	1	2	0	0	1	2	3	1	0	
1	2	3	2	3	2	3	2	1	3	2	3	2	2	
2	1	3	3	1	3	1	3	2	1	3	2	3	3	
3	0	2	0	0	0	0	0	0	1	0	0	0	0	
4	2	2	2	3	3	2	2	2	3	3	3	3	2	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
28346	0	1	0	1	1	0	0	1	1	0	0	0	0	
28347	2	2	3	3	3	2	3	3	3	3	3	2	3	
28348	1	0	0	1	0	0	0	1	0	1	0	0	0	
28349	1	2	0	3	0	1	1	1	2	1	1	0	1	
28350	1	3	0	2	3	3	3	1	1	1	2	1	3	

28351 rows × 60 columns

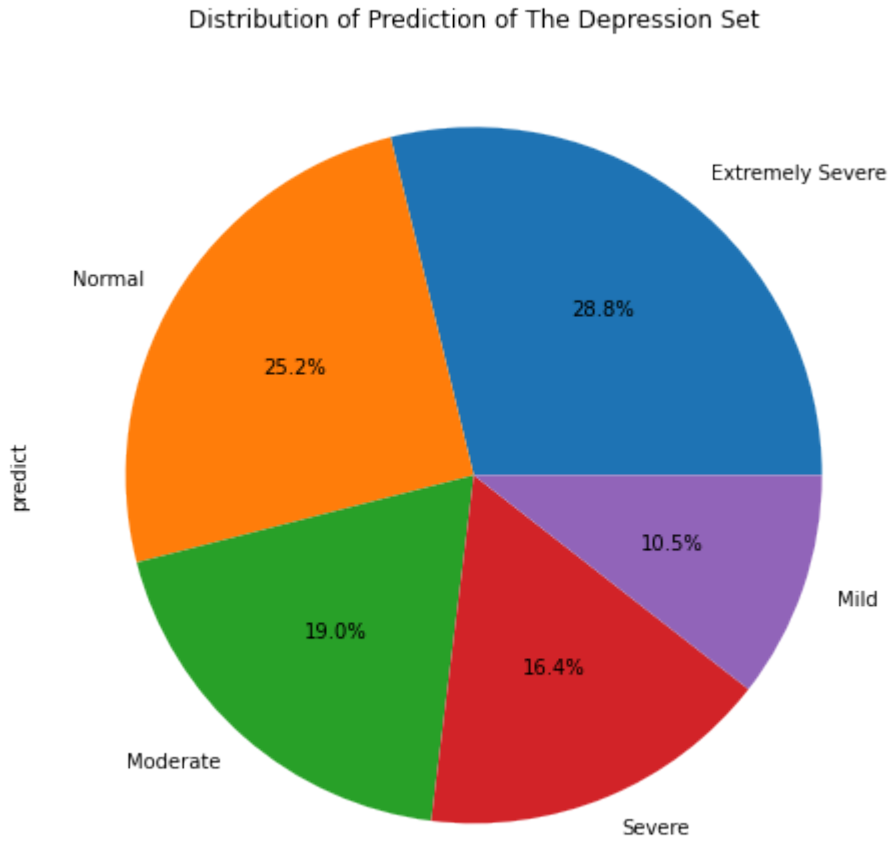
In [337]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Depression, x=Depression.sort_values('predict').predict
3 plt.title('People Prediction of Depression Level',fontsize=15)
```

Out[337]: Text(0.5, 1.0, 'People Prediction of Depression Level')



In [338]:
```
1 value_counts = Depression['predict'].value_counts().sort_index()
```

In [339]:
```
plt.figure(figsize=(8, 8))
Depression['predict'].value_counts().plot.pie(autopct='%1.1f%%', startangl
plt.title('Distribution of Prediction of The Depression Set')
plt.show()
```



in Anxiety Set

In [340]:
```
Anxiety=pd.merge(anxiety, dass_part2,how='left',left_index=True,right_inde
Anxiety.head()
```

Out[340]:

	Q2A	Q4A	Q7A	Q9A	Q15A	Q19A	Q20A	Q23A	Q25A	Q28A	Q30A	Q36A	Q40A	Q41A
0	2	0	3	2	1	0	1	0	0	0	2	0	3	3
1	1	3	3	3	3	3	3	3	3	3	3	3	3	3
2	0	2	2	2	2	0	2	2	1	1	2	1	1	1
3	0	0	1	0	1	0	1	0	1	0	0	0	0	0
4	3	3	3	3	3	3	3	3	1	3	2	3	3	3

In [341]:

```
def predict_anxiety(x):
    if x<=7:
        return 'Normal'
    if  8<=x<=9:
        return 'Mild'
    if 10<=x<=14:
        return 'Moderate'
    if 15<=x<=19:
        return 'Severe'
    if x>19:
        return 'Extremely Severe'
```

In [342]:

```
Anxiety['predict']=Anxiety['Total_Count'].apply(predict_anxiety)
```

In [343]:

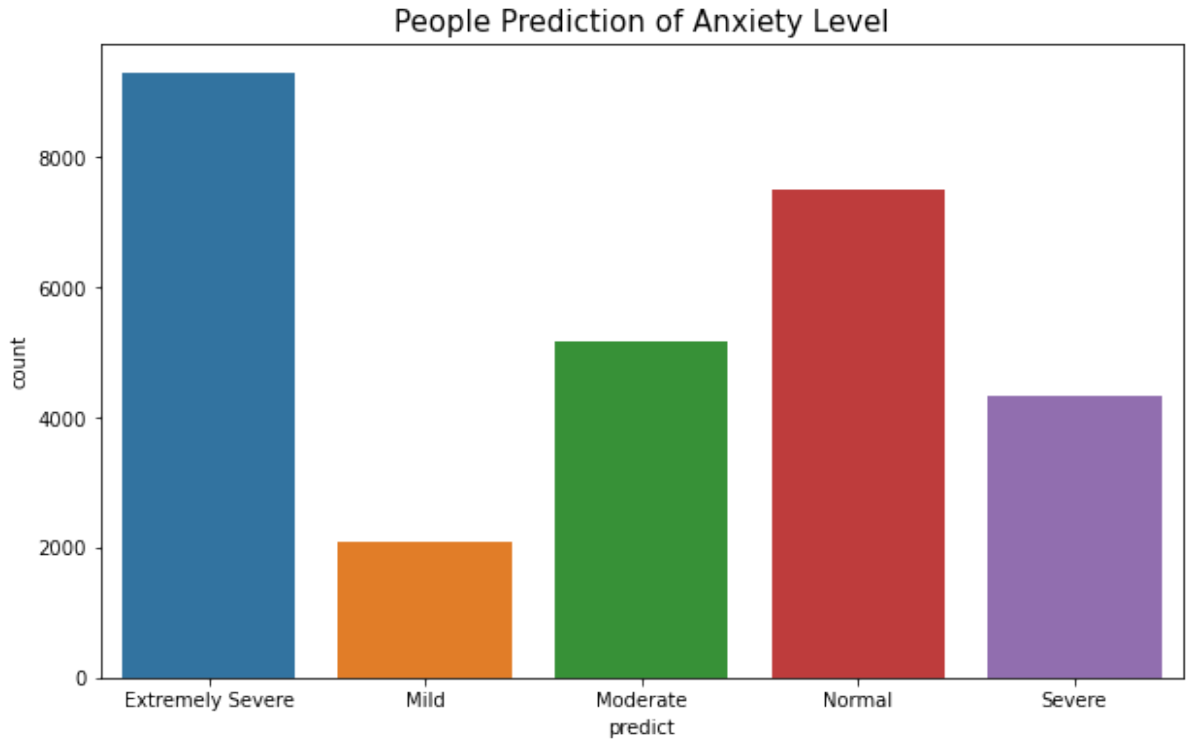
```
Anxiety
```

Out[343]:

	Q2A	Q4A	Q7A	Q9A	Q15A	Q19A	Q20A	Q23A	Q25A	Q28A	Q30A	Q36A	Q40A
0	2	0	3	2	1	0	1	0	0	0	2	0	3
1	1	3	3	3	3	3	3	3	3	3	3	3	3
2	0	2	2	2	2	0	2	2	1	1	2	1	1
3	0	0	1	0	1	0	1	0	1	0	0	0	0
4	3	3	3	3	3	3	3	3	1	3	2	3	3
...	...	...	...	...	...	...	...	...	...	...	...	...	...
28346	0	0	0	0	0	1	0	0	0	0	1	0	0
28347	3	3	3	2	3	3	3	2	2	2	2	2	2
28348	0	0	0	1	0	0	0	0	0	0	0	0	0
28349	0	1	2	2	0	0	1	0	0	2	0	1	1

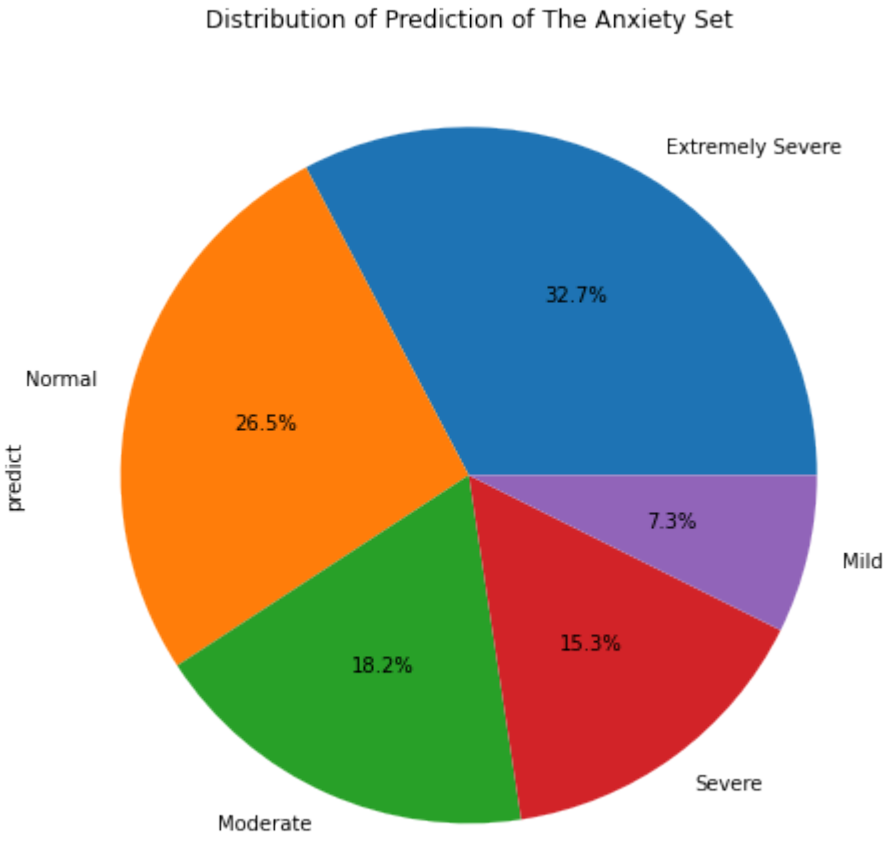
In [344]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Anxiety, x=Anxiety.sort_values('predict').predict)
3 plt.title('People Prediction of Anxiety Level',fontsize=15)
```

Out[344]: Text(0.5, 1.0, 'People Prediction of Anxiety Level')



In [345]:
```
1 value_counts = Anxiety['predict'].value_counts().sort_index()
```

In [346]:
```
plt.figure(figsize=(8, 8))
Anxiety['predict'].value_counts().plot.pie(autopct='%1.1f%%', startangle=0
plt.title('Distribution of Prediction of The Anxiety Set')
plt.show()
```



in Stress Set

In [347]:
```
Stress=pd.merge(stress,dass_part2,how='left',left_index=True,right_index=T
Stress.head()
```

Out[347]:

	Q1A	Q6A	Q8A	Q11A	Q12A	Q14A	Q18A	Q22A	Q27A	Q29A	Q32A	Q33A	Q35A	Q39A
0	1	2	1	1	0	3	0	0	3	2	0	1	0	2
1	1	1	3	1	3	3	3	2	1	1	3	3	2	2
2	0	0	2	0	1	1	1	0	0	1	1	3	1	3
3	0	1	0	1	0	1	1	0	1	0	0	0	0	1
4	3	3	3	3	3	2	3	3	1	3	1	3	1	1

In [348]:
```
def predict_stress(x):
    if x<=14:
        return 'Normal'
    if  15<=x<=18:
        return 'Mild'
    if 19<=x<=25:
        return 'Moderate'
    if 26<=x<=33:
        return 'Severe'
    if x>=34:
        return 'Extremely Severe'
```

In [349]:
```
Stress['predict']=Stress['Total_Count'].apply(predict_stress)
```

In [350]:
```
Stress
```

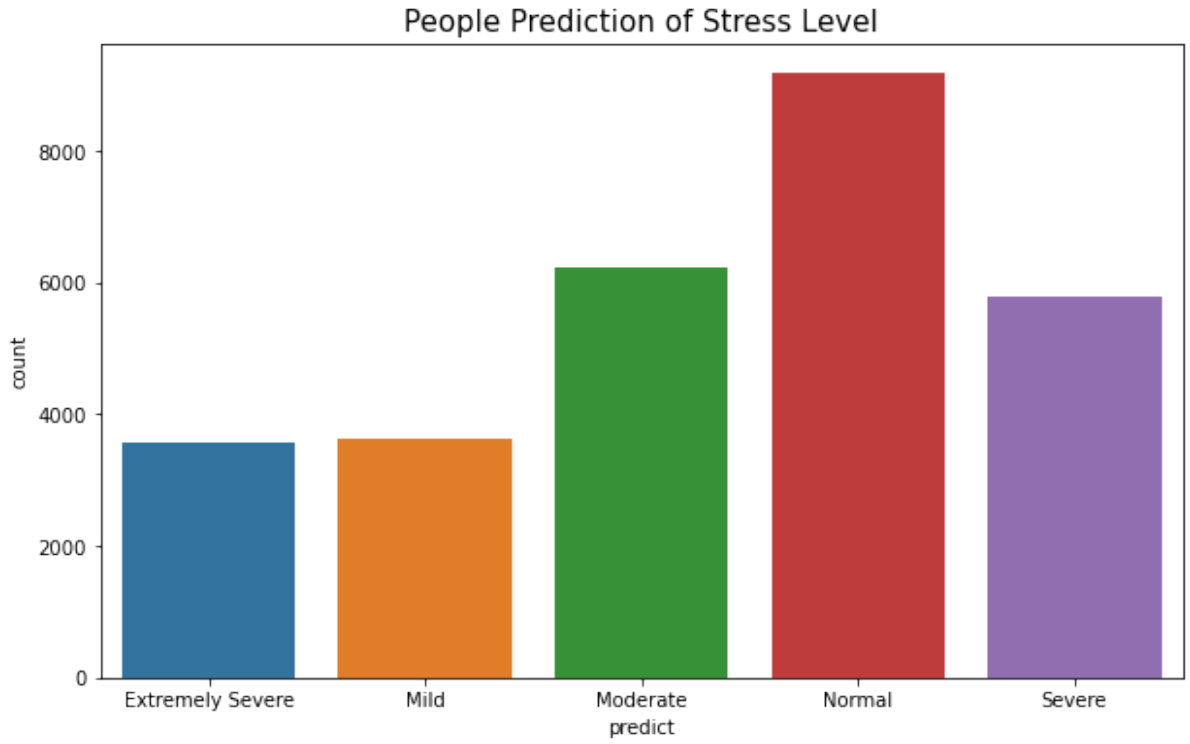
Out[350]:

	Q1A	Q6A	Q8A	Q11A	Q12A	Q14A	Q18A	Q22A	Q27A	Q29A	Q32A	Q33A	Q35A	Q3
0	1	2	1	1	0	3	0	0	3	2	0	1	0	
1	1	1	3	1	3	3	3	2	1	1	3	3	2	
2	0	0	2	0	1	1	1	0	0	1	1	3	1	
3	0	1	0	1	0	1	1	0	1	0	0	0	0	
4	3	3	3	3	3	2	3	3	1	3	1	3	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
28346	1	1	1	1	1	1	1	1	1	1	1	1	1	
28347	2	3	3	3	3	3	2	3	2	2	2	2	2	
28348	1	0	0	0	0	0	0	0	1	1	0	1	0	
28349	2	2	3	2	2	3	2	3	3	2	2	3	2	
28350	1	1	0	2	0	0	2	1	2	2	1	1	1	

28351 rows × 60 columns

In [351]:
```
plt.figure(figsize=(10,6))
sns.countplot(data=Depression, x=Stress.sort_values('predict').predict)
plt.title('People Prediction of Stress Level',fontsize=15)
```

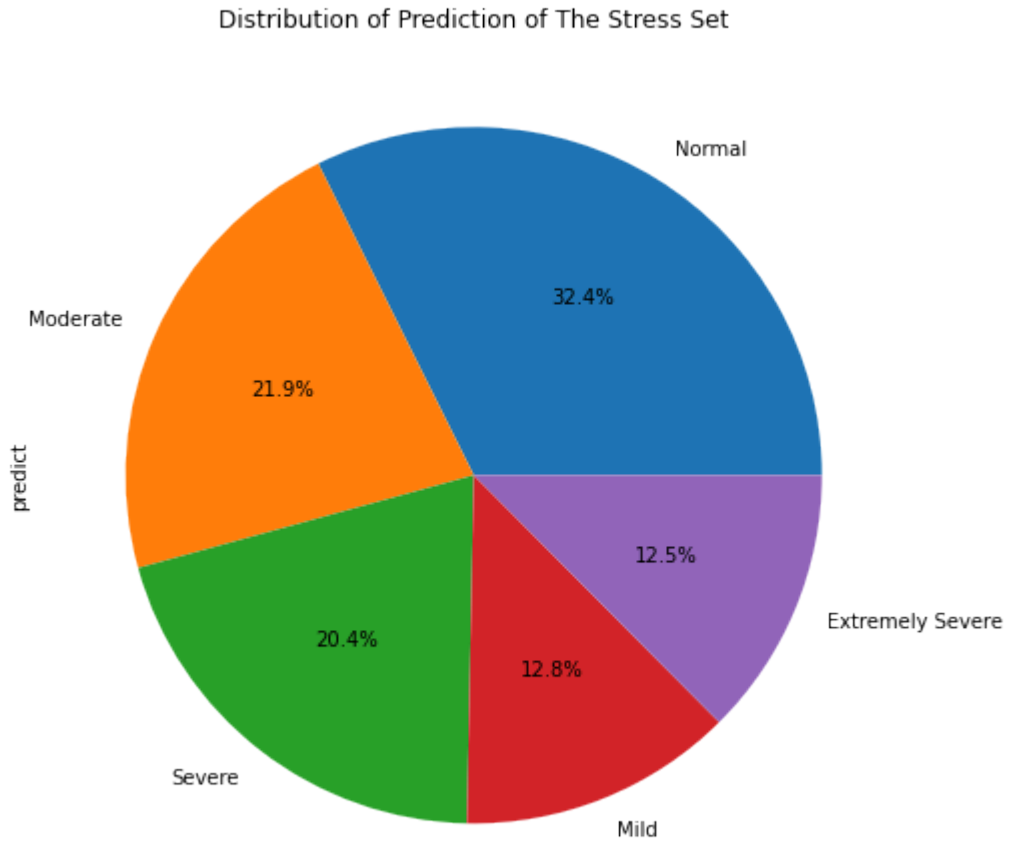
Out[351]: Text(0.5, 1.0, 'People Prediction of Stress Level')



In [352]:
```
value_counts = Stress['predict'].value_counts().sort_index()
```

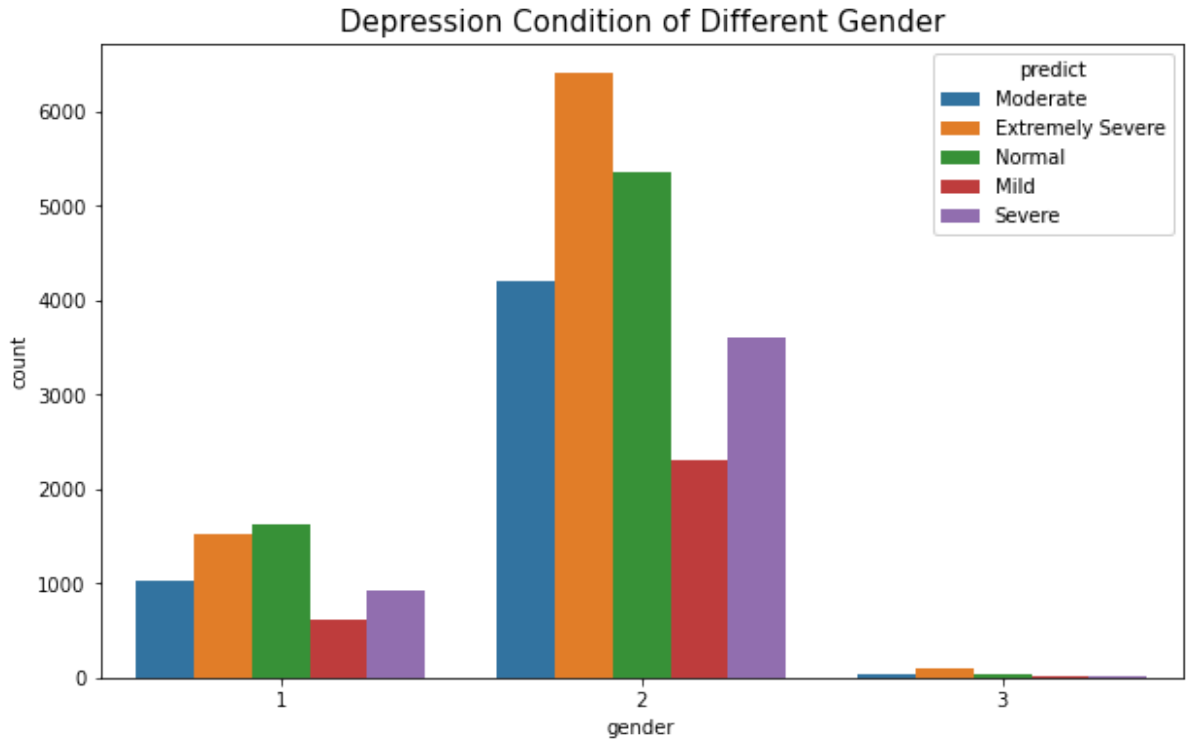
In [353]:

```
plt.figure(figsize=(8, 8))
Stress['predict'].value_counts().plot.pie(autopct='%1.1f%%', startangle=0)
plt.title('Distribution of Prediction of The Stress Set')
plt.show()
```



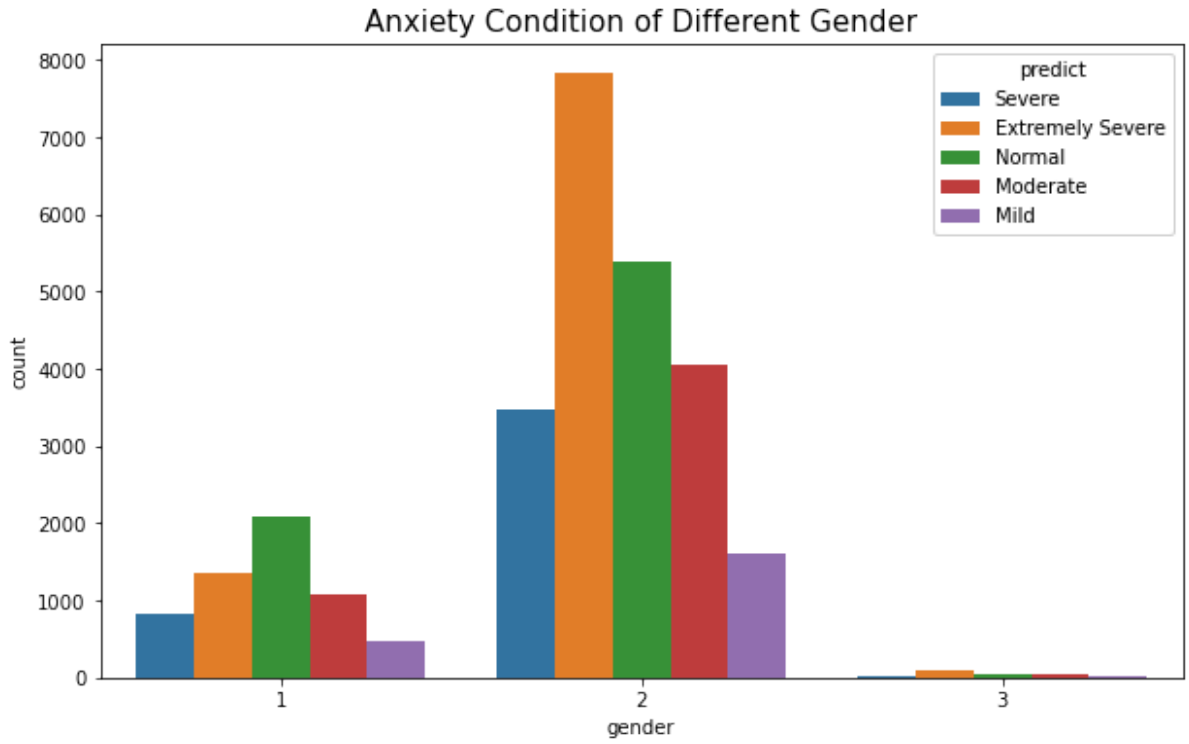
In [354]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Depression, x=Depression.sort_values('gender').gender,h
3 plt.title('Depression Condition of Different Gender',fontsize=15)
```

Out[354]: Text(0.5, 1.0, 'Depression Condition of Different Gender')



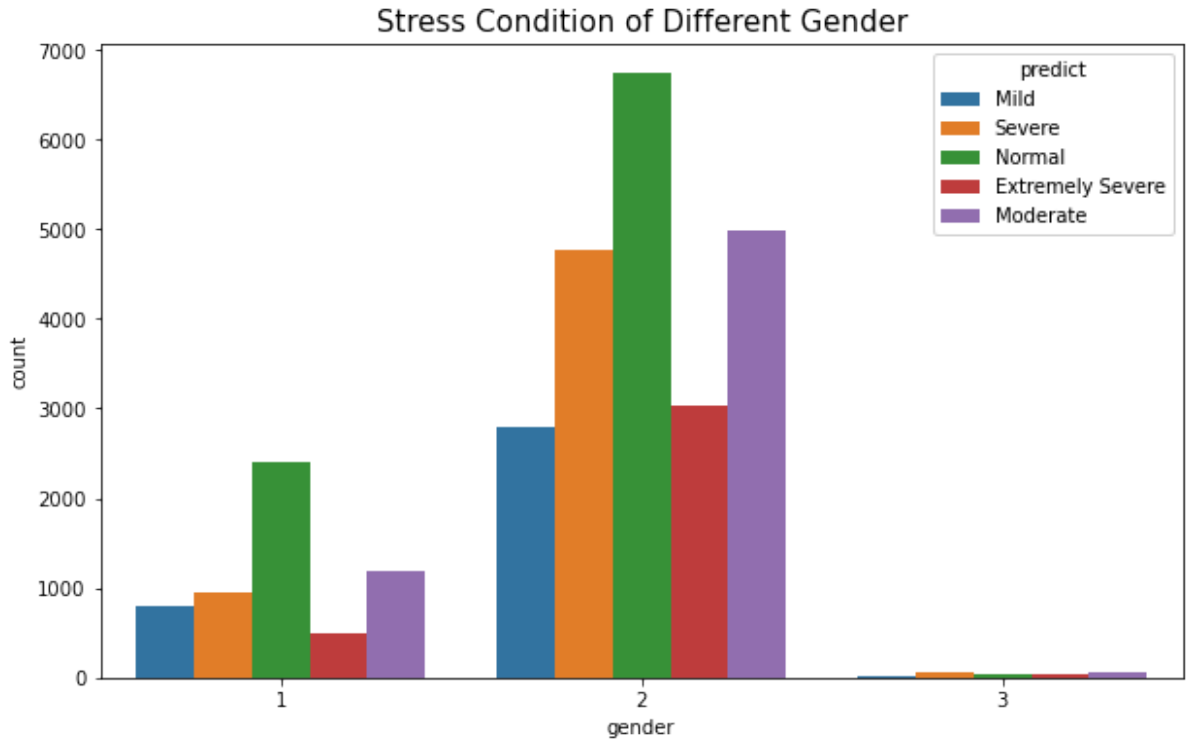
In [355]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Anxiety, x=Anxiety.sort_values('gender').gender,hue=Anx
3 plt.title('Anxiety Condition of Different Gender',fontsize=15)
```

Out[355]: Text(0.5, 1.0, 'Anxiety Condition of Different Gender')



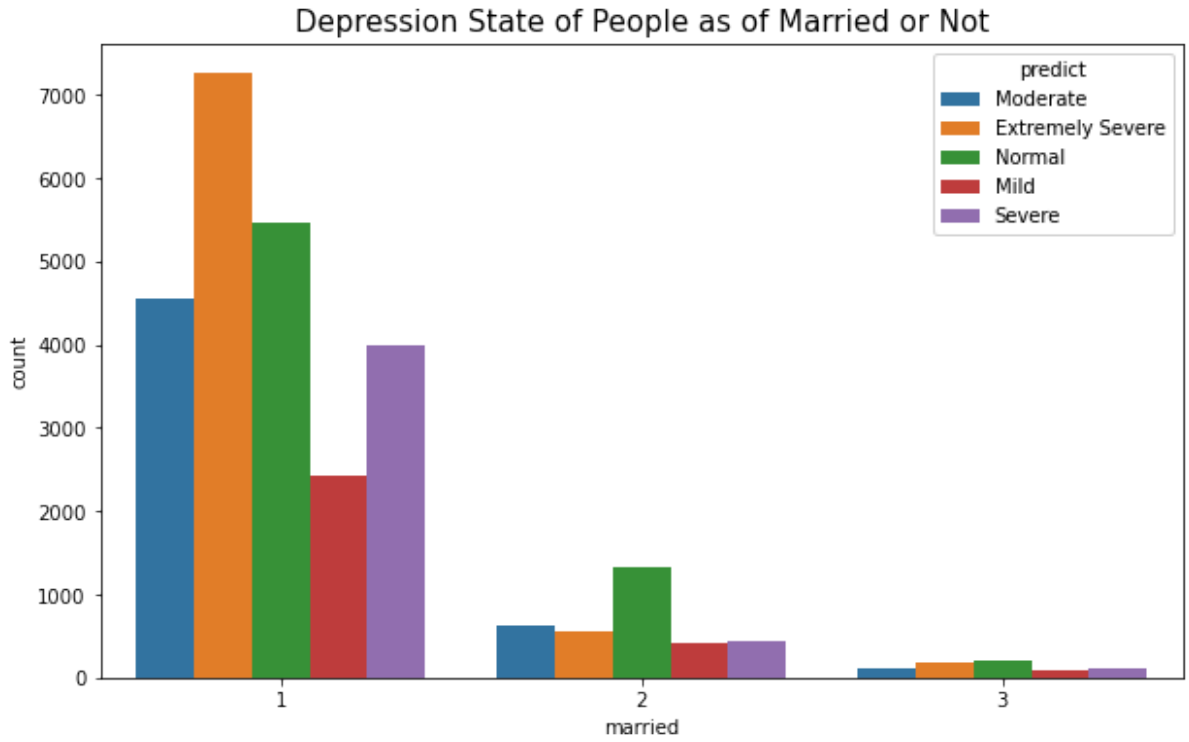
In [356]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Stress, x=Stress.sort_values('gender').gender,hue=Stres
3 plt.title('Stress Condition of Different Gender',fontsize=15)
```

Out[356]: Text(0.5, 1.0, 'Stress Condition of Different Gender')



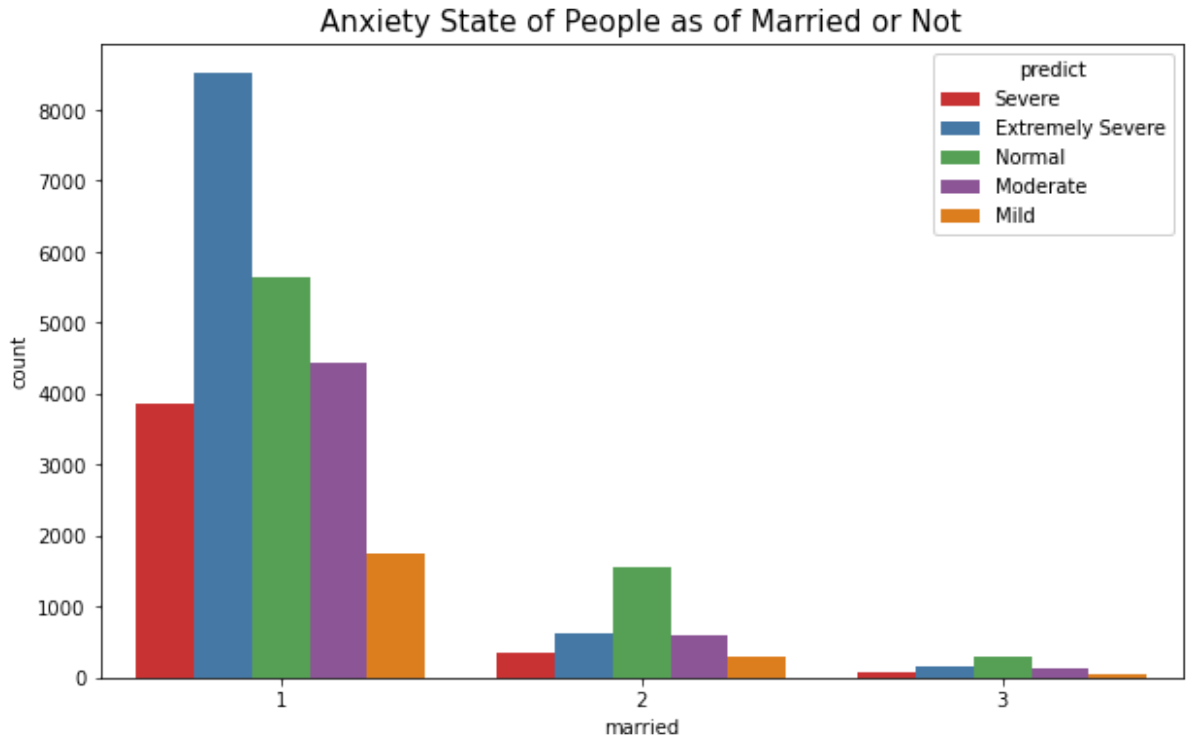
In [357]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Depression, x=Depression.sort_values('married').married
3 plt.title('Depression State of People as of Married or Not',fontsize=15)
```

Out[357]: Text(0.5, 1.0, 'Depression State of People as of Married or Not')



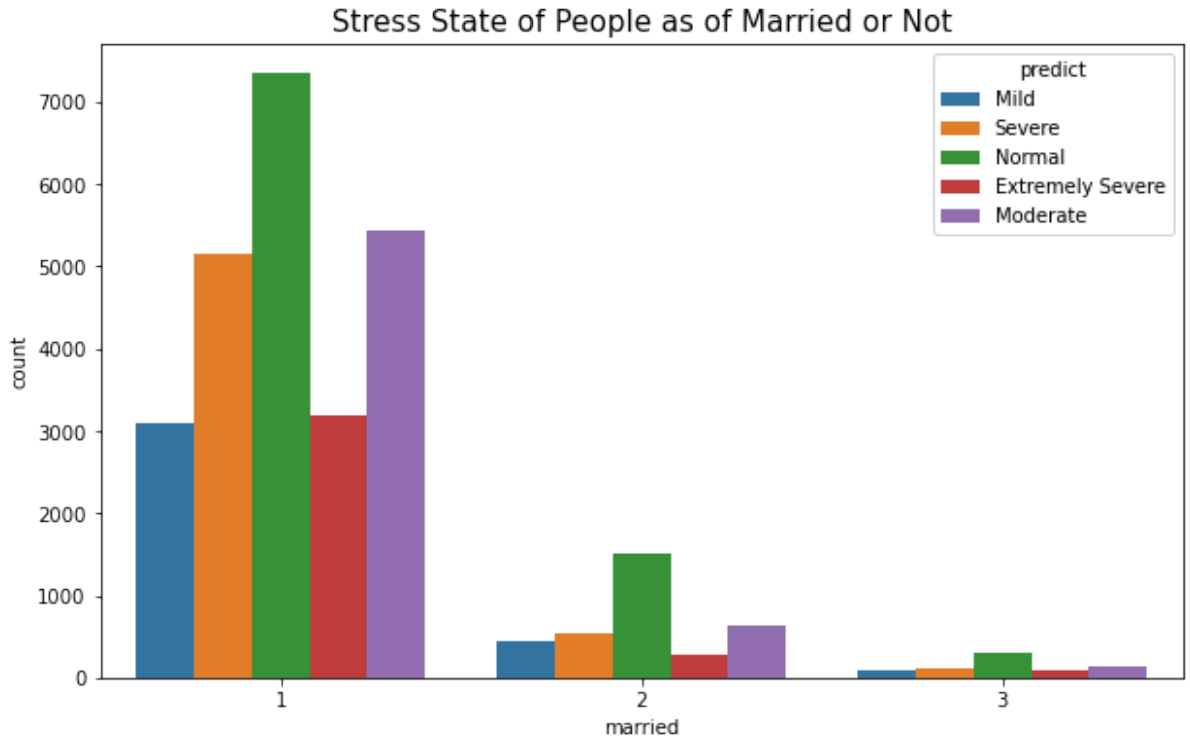
In [358]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Anxiety, x=Anxiety.sort_values('married').married,hue=A
3 plt.title('Anxiety State of People as of Married or Not',fontsize=15)
```

Out[358]: Text(0.5, 1.0, 'Anxiety State of People as of Married or Not')



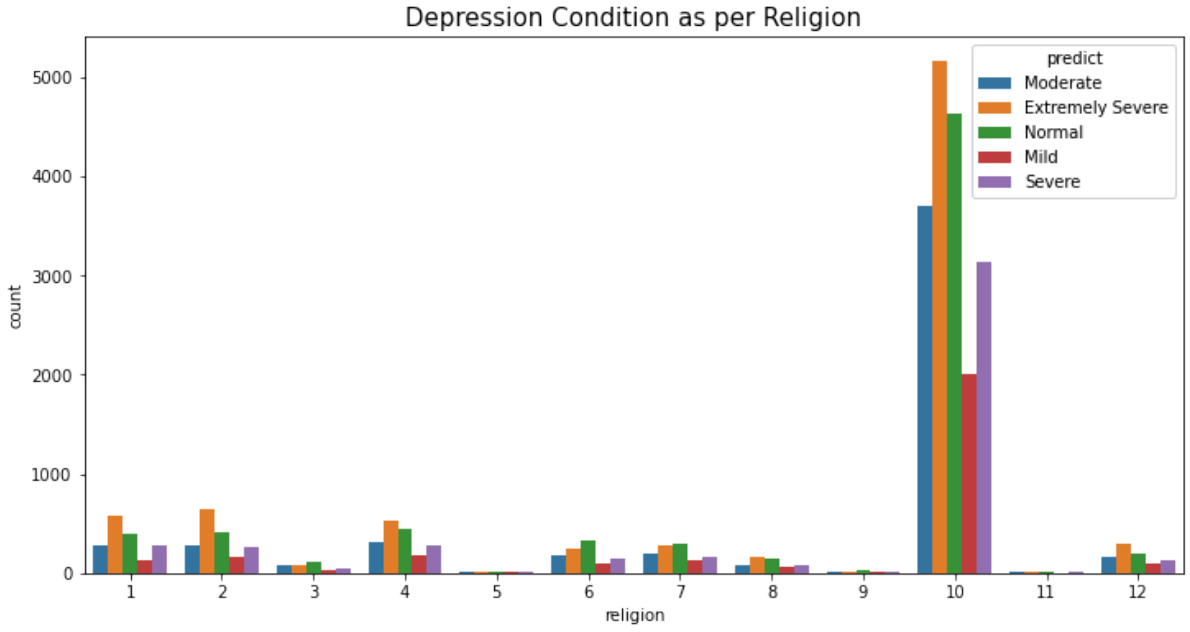
In [359]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Stress, x=Stress.sort_values('married').married,hue=Str
3 plt.title('Stress State of People as of Married or Not',fontsize=15)
```

Out[359]: Text(0.5, 1.0, 'Stress State of People as of Married or Not')



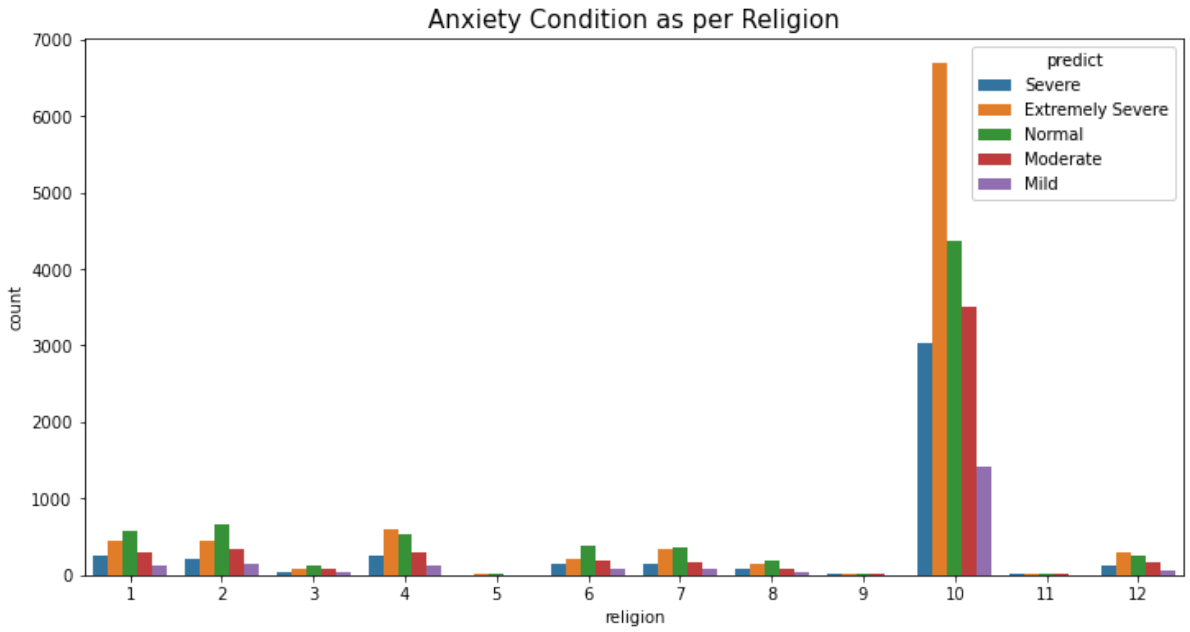
In [360]:
```
1 plt.figure(figsize=(12,6))
2 a=sns.countplot(data=Depression, x=Depression.sort_values('religion').reli
3 plt.title('Depression Condition as per Religion',fontsize=15)
```

Out[360]: Text(0.5, 1.0, 'Depression Condition as per Religion')



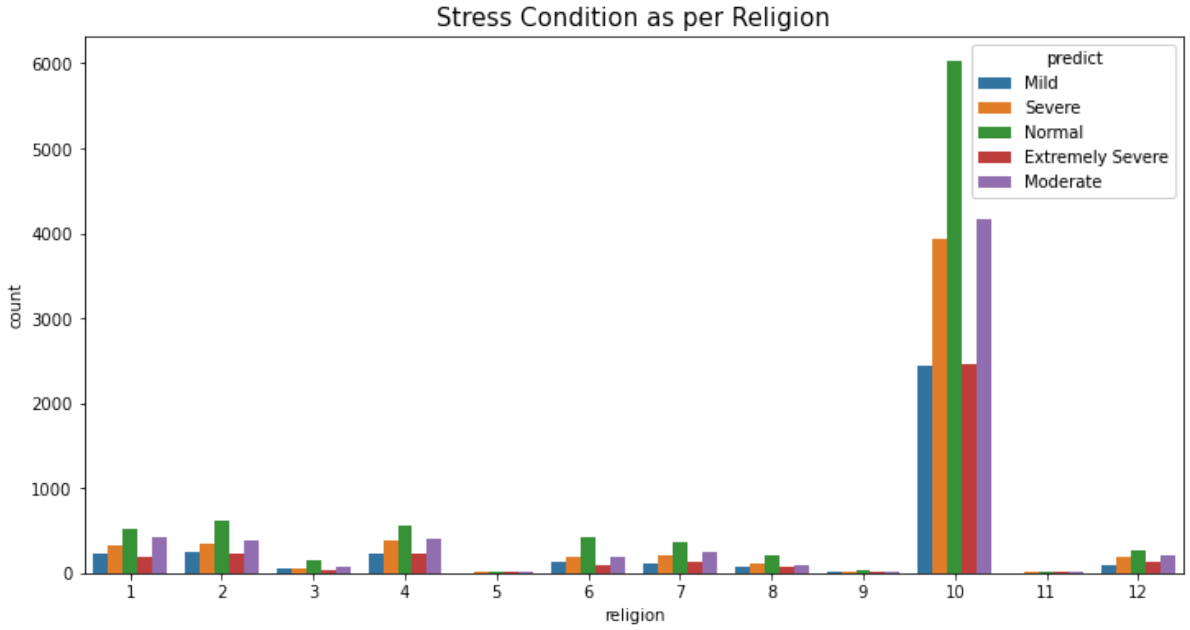
In [361]:
```
1 plt.figure(figsize=(12,6))
2 sns.countplot(data=Anxiety, x=Anxiety.sort_values('religion').religion,hue
3 plt.title('Anxiety Condition as per Religion',fontsize=15)
```

Out[361]: Text(0.5, 1.0, 'Anxiety Condition as per Religion')



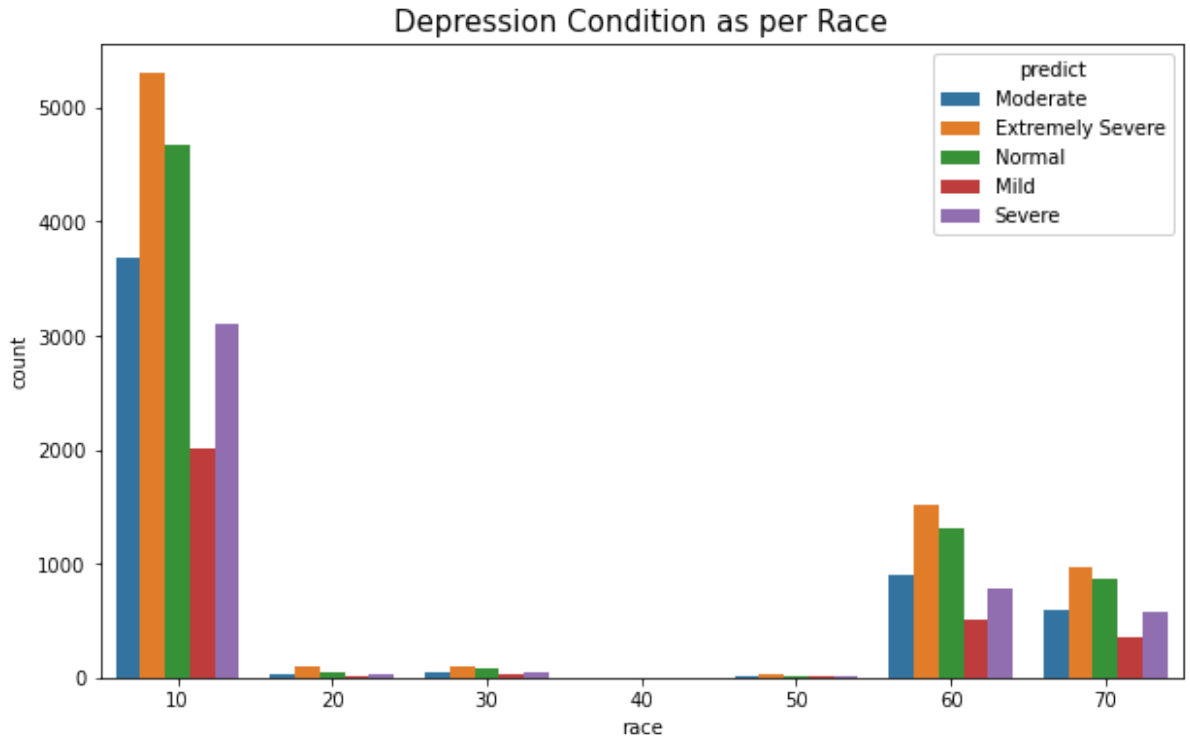
In [362]:
```
1 plt.figure(figsize=(12,6))
2 sns.countplot(data=Stress, x=Stress.sort_values('religion').religion,hue=S
3 plt.title('Stress Condition as per Religion',fontsize=15)
```

Out[362]: Text(0.5, 1.0, 'Stress Condition as per Religion')



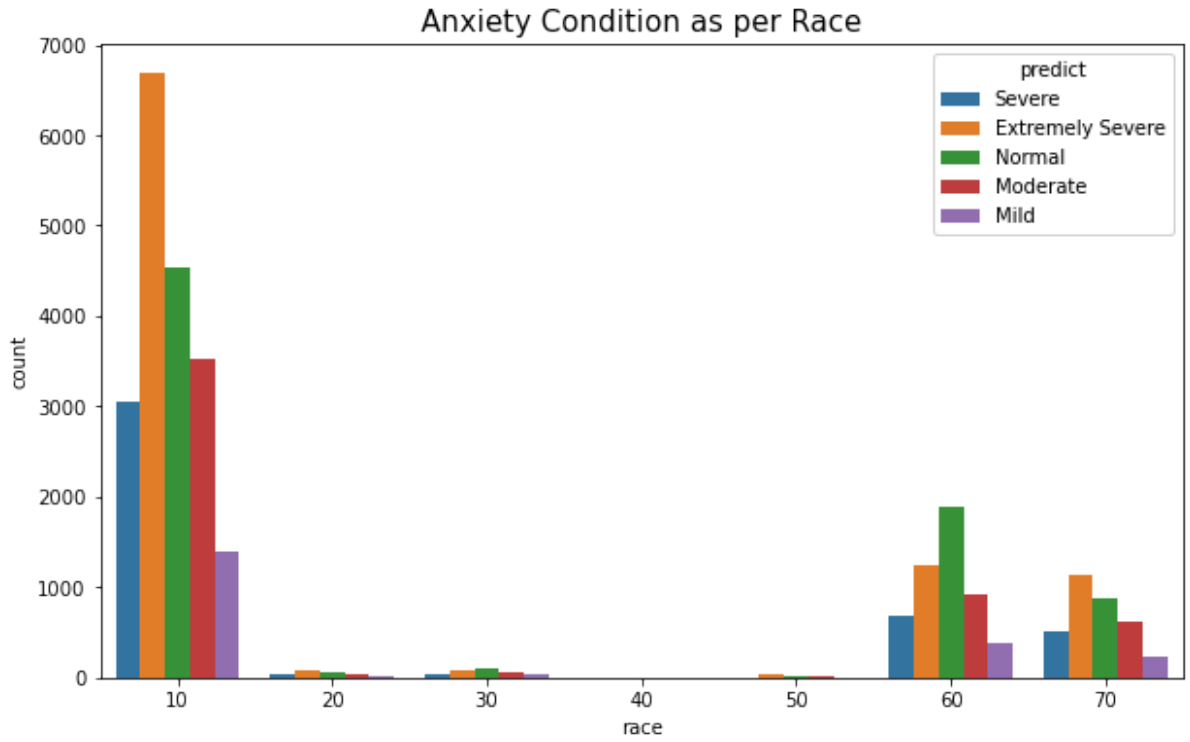
In [363]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Depression, x=Depression.sort_values('race').race,hue=D
3 plt.title('Depression Condition as per Race',fontsize=15)
```

Out[363]: Text(0.5, 1.0, 'Depression Condition as per Race')



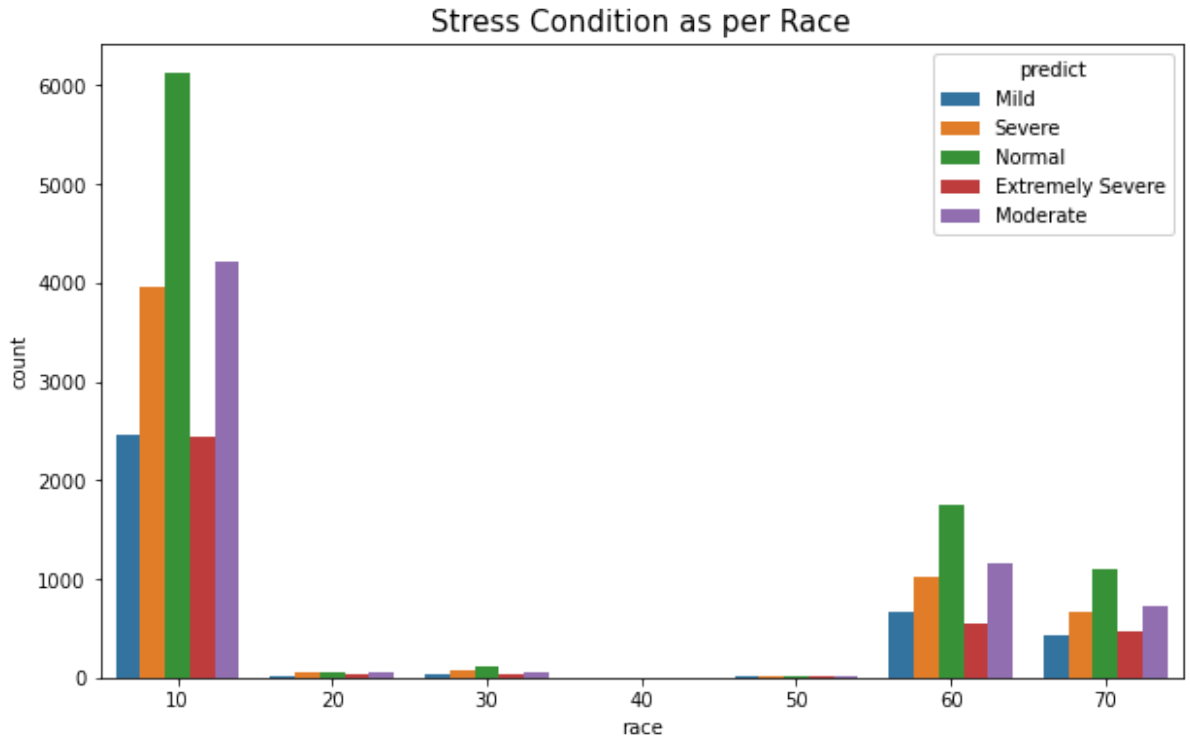
In [364]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Anxiety, x=Anxiety.sort_values('race').race,hue=Anxiety
3 plt.title('Anxiety Condition as per Race',fontsize=15)
```

Out[364]: Text(0.5, 1.0, 'Anxiety Condition as per Race')



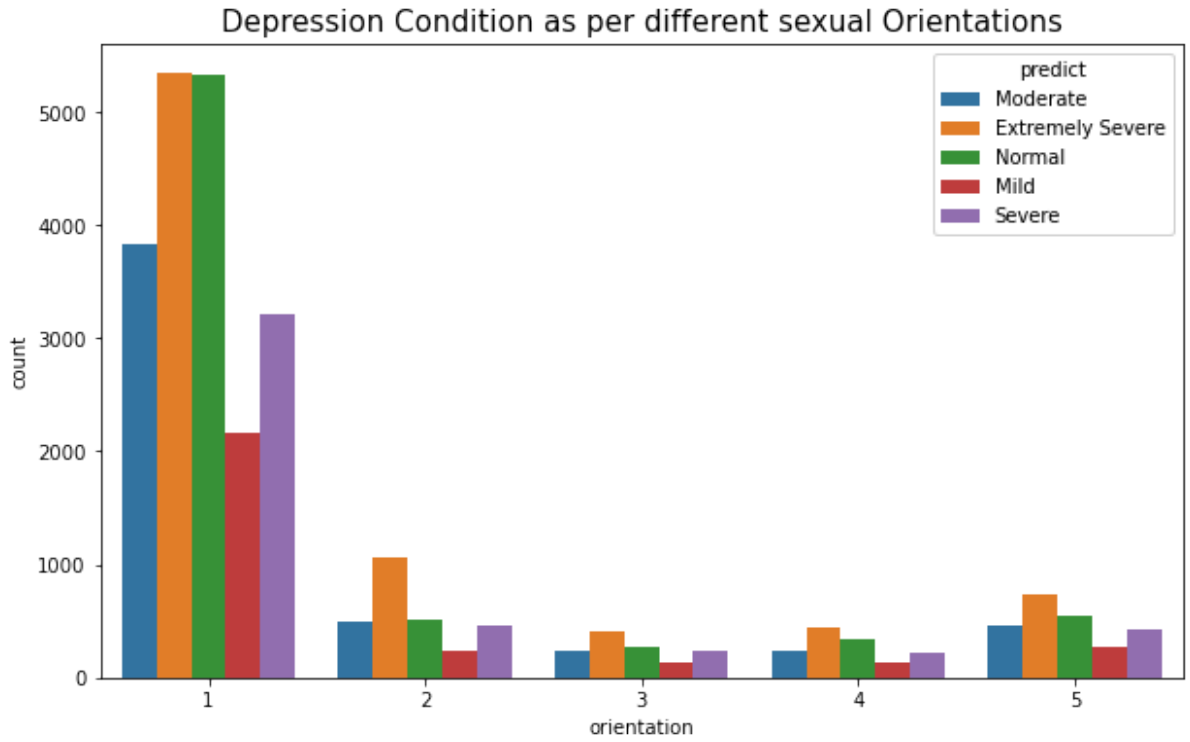
In [365]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Stress, x=Stress.sort_values('race').race,hue=Stress['p
3 plt.title('Stress Condition as per Race',fontsize=15)
```

Out[365]: Text(0.5, 1.0, 'Stress Condition as per Race')



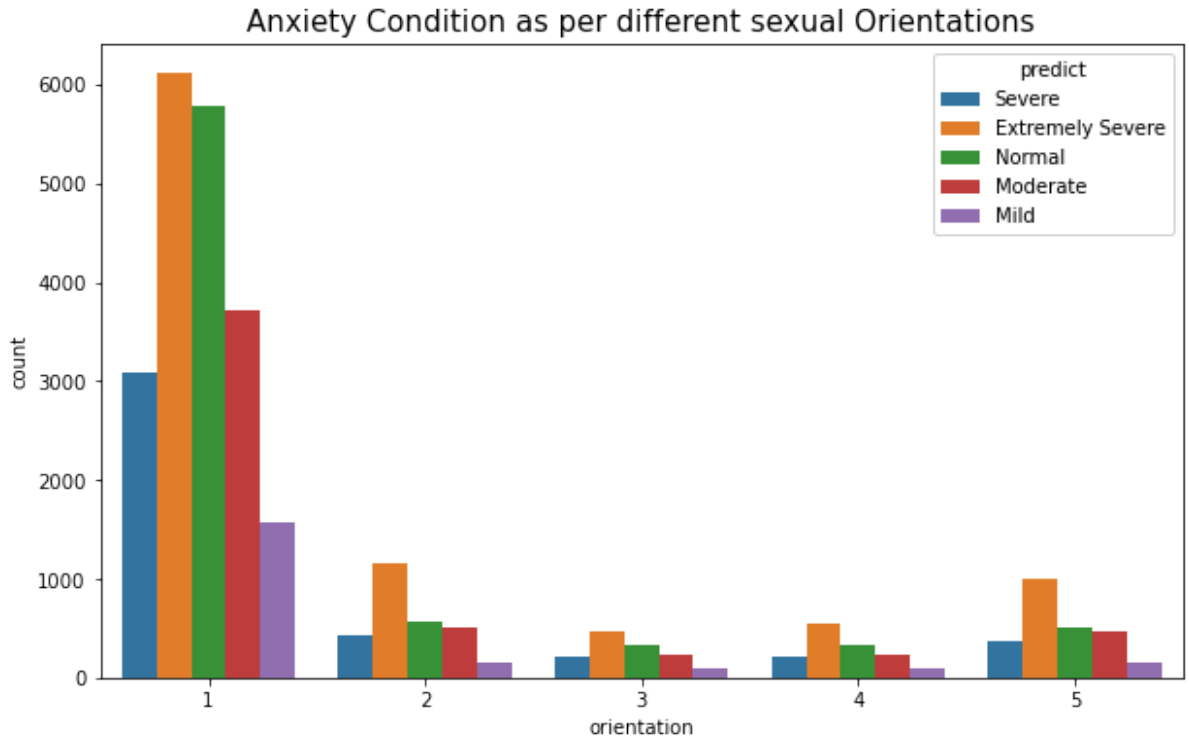
In [366]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Depression, x=Depression.sort_values('orientation').ori
3 plt.title('Depression Condition as per different sexual Orientations',font
```

Out[366]: Text(0.5, 1.0, 'Depression Condition as per different sexual Orientations')



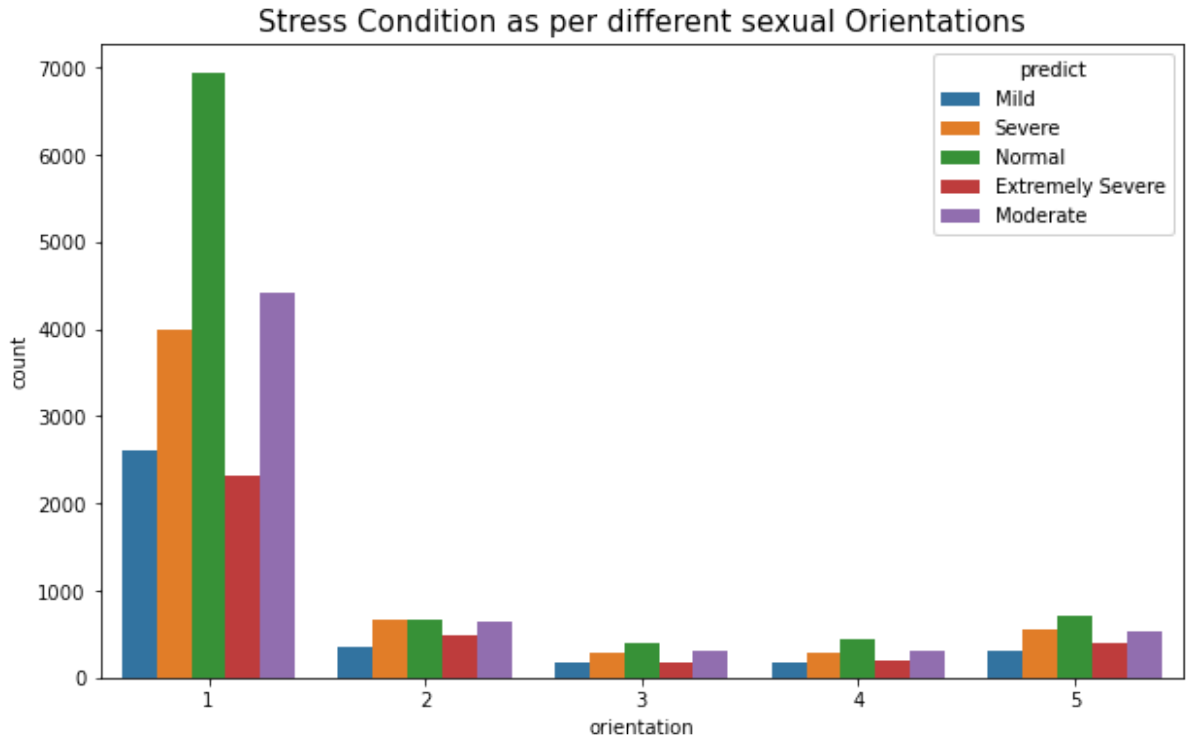
In [367]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Anxiety, x=Anxiety.sort_values('orientation').orientati
3 plt.title('Anxiety Condition as per different sexual Orientations',fontsiz
```

Out[367]: Text(0.5, 1.0, 'Anxiety Condition as per different sexual Orientations')



In [368]:
```
plt.figure(figsize=(10,6))
sns.countplot(data=Stress, x=Stress.sort_values('orientation').orientation
plt.title('Stress Condition as per different sexual Orientations',fontsize
```

Out[368]: Text(0.5, 1.0, 'Stress Condition as per different sexual Orientations')



In [369]:
```
Depression
```

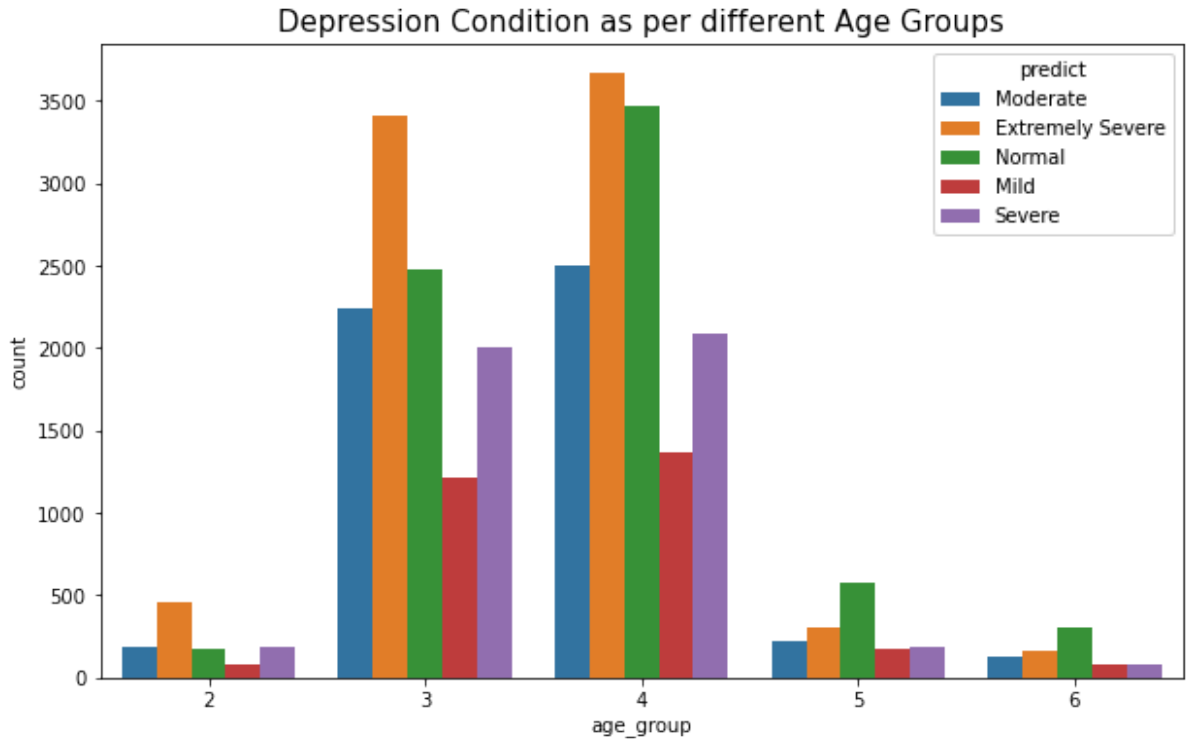
Out[369]:

	Q3A	Q5A	Q10A	Q13A	Q16A	Q17A	Q21A	Q24A	Q26A	Q31A	Q34A	Q37A	Q38A	
0	1	2	2	0	1	2	0	0	1	2	3	1	0	
1	2	3	2	3	2	3	2	1	3	2	3	2	2	
2	1	3	3	1	3	1	3	2	1	3	2	3	3	
3	0	2	0	0	0	0	0	0	1	0	0	0	0	
4	2	2	2	3	3	2	2	2	3	3	3	3	2	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
28346	0	1	0	1	1	0	0	1	1	0	0	0	0	
28347	2	2	3	3	3	2	3	3	3	3	3	2	3	
28348	1	0	0	1	0	0	0	1	0	1	0	0	0	
28349	1	2	0	3	0	1	1	1	2	1	1	0	1	
28350	1	3	0	2	3	3	3	1	1	1	2	1	3	

28351 rows × 60 columns

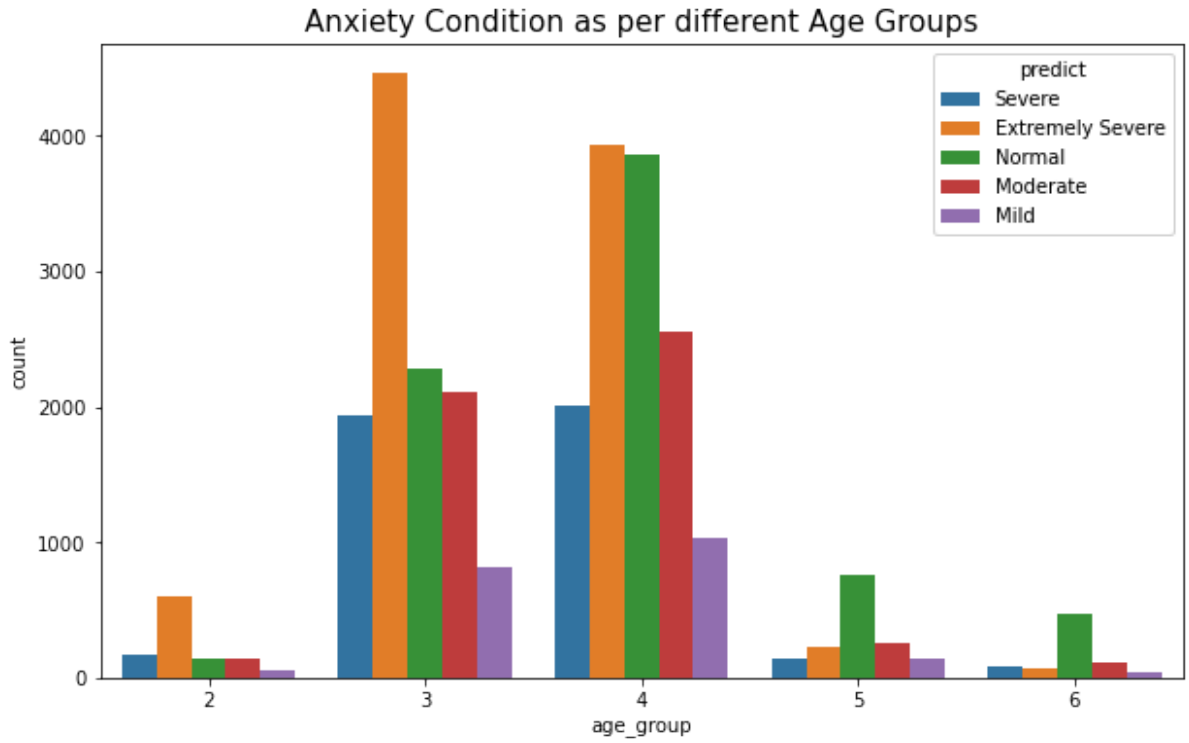
In [370]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Depression, x=Depression.sort_values('age_group').age_g
3 plt.title('Depression Condition as per different Age Groups',fontsize=15)
```

Out[370]: Text(0.5, 1.0, 'Depression Condition as per different Age Groups')



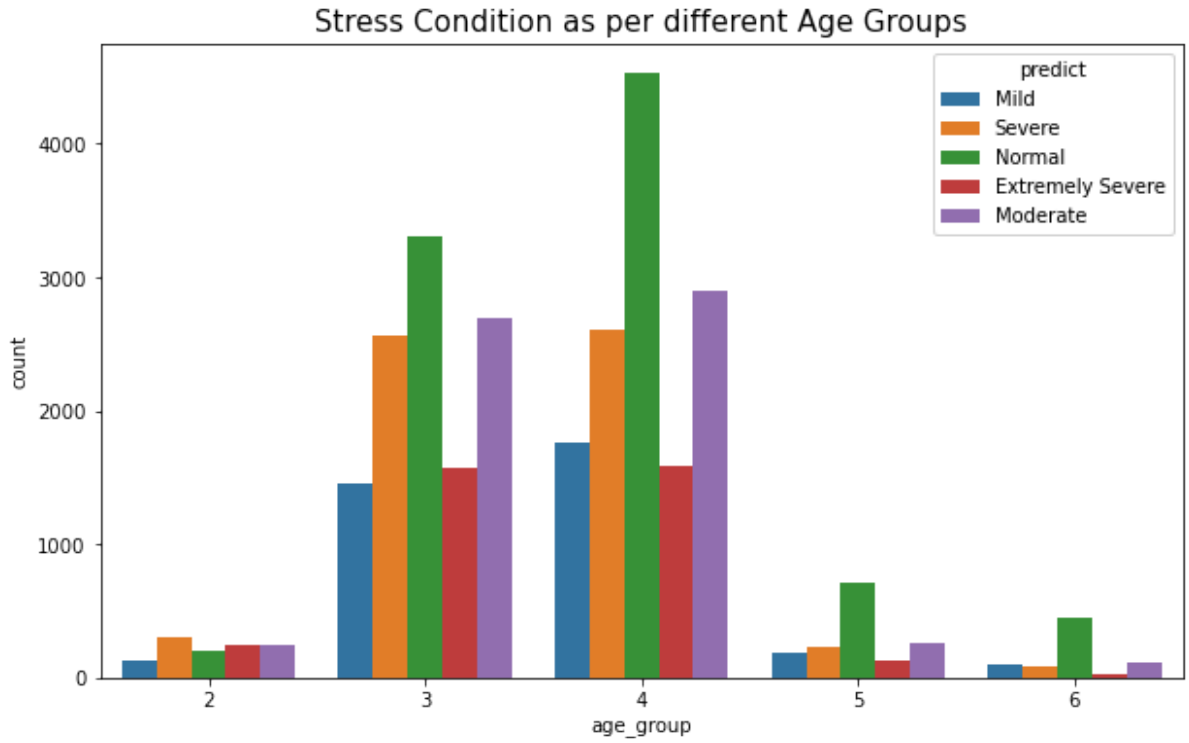
In [371]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Anxiety, x=Anxiety.sort_values('age_group').age_group,hu
3 plt.title('Anxiety Condition as per different Age Groups',fontsize=15)
```

Out[371]: Text(0.5, 1.0, 'Anxiety Condition as per different Age Groups')



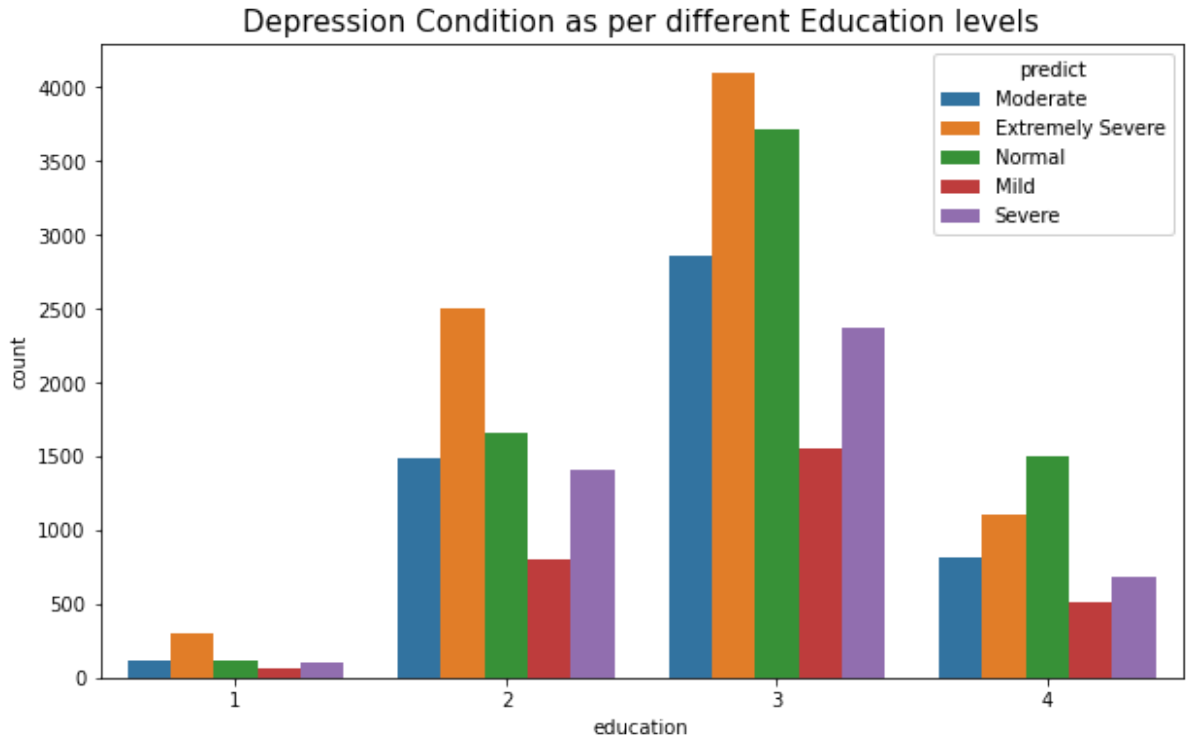
In [372]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Stress, x=Stress.sort_values('age_group').age_group,hue
3 plt.title('Stress Condition as per different Age Groups',fontsize=15)
```

Out[372]: Text(0.5, 1.0, 'Stress Condition as per different Age Groups')



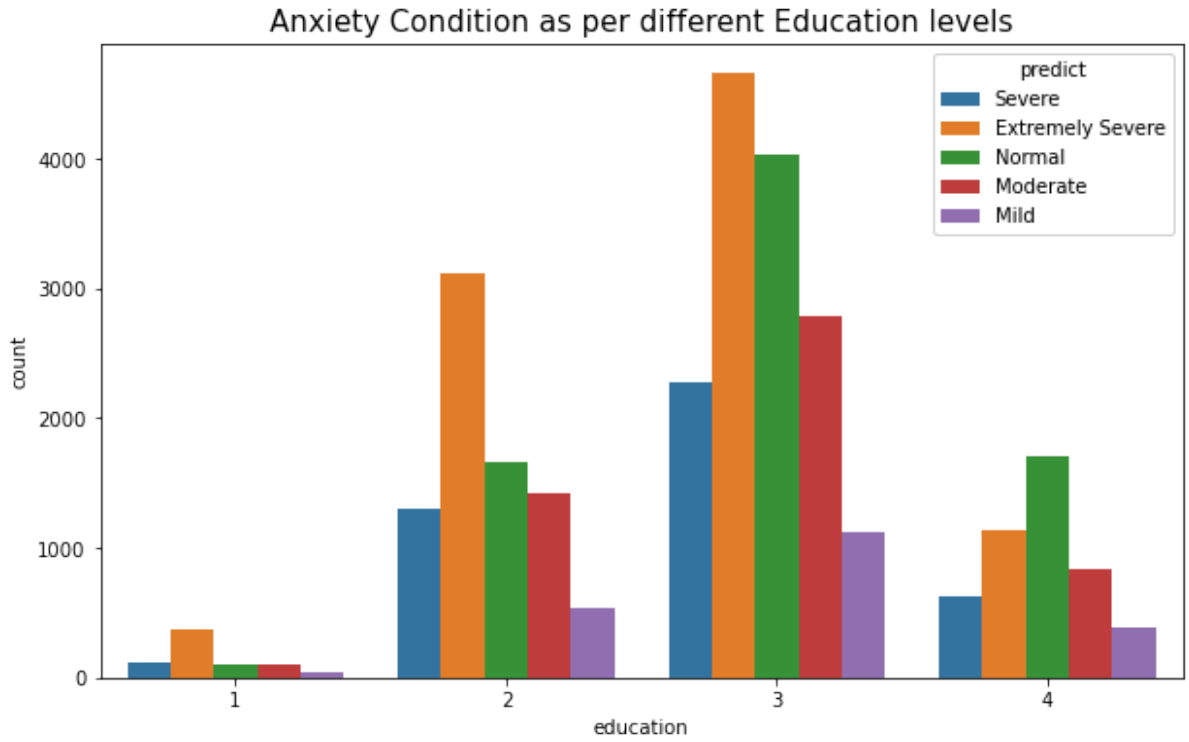
In [373]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Depression, x=Depression.sort_values('education').educa
3 plt.title('Depression Condition as per different Education levels',fontsiz
```

Out[373]: Text(0.5, 1.0, 'Depression Condition as per different Education levels')



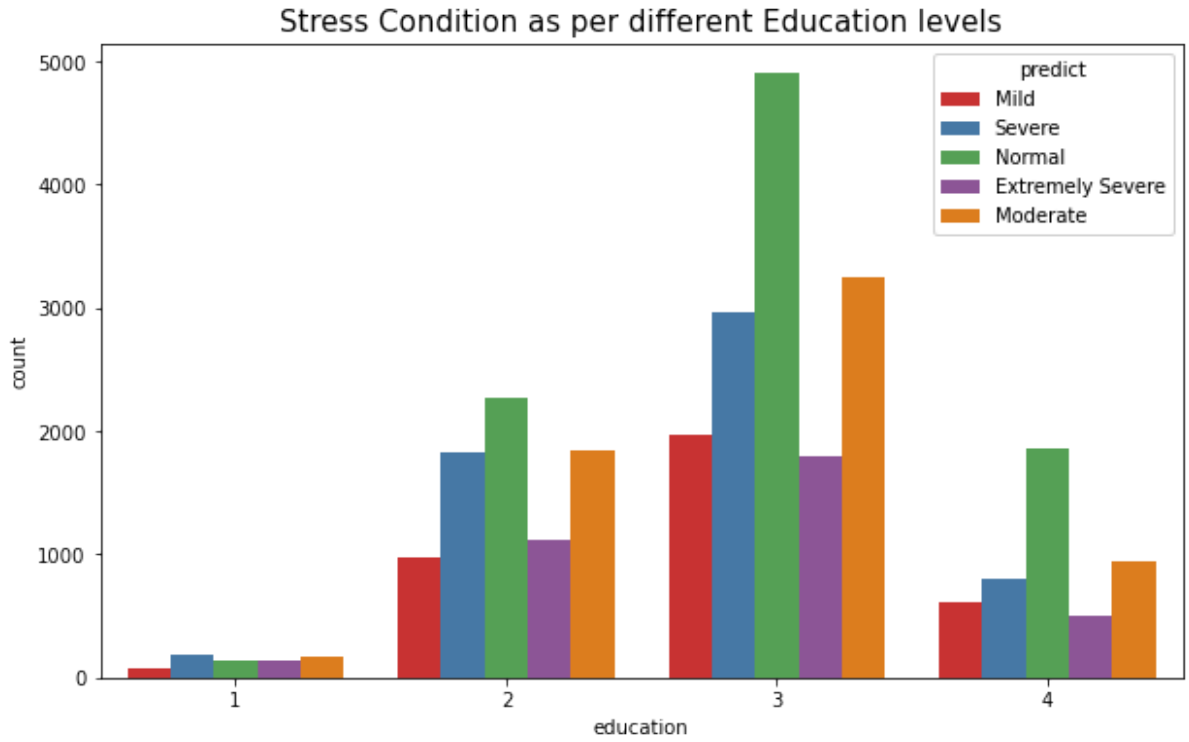
In [374]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Anxiety, x=Anxiety.sort_values('education').education,h
3 plt.title('Anxiety Condition as per different Education levels',fontsize=1
```

Out[374]: Text(0.5, 1.0, 'Anxiety Condition as per different Education levels')



In [375]:
```
1 plt.figure(figsize=(10,6))
2 sns.countplot(data=Stress, x=Stress.sort_values('education').education,hue
3 plt.title('Stress Condition as per different Education levels',fontsize=15
```

Out[375]: Text(0.5, 1.0, 'Stress Condition as per different Education levels')



In [376]:

```
columns_to_check = Depression.columns[0::]
plot_null_values(Depression, columns_to_check)
```

Null values in the specified columns:

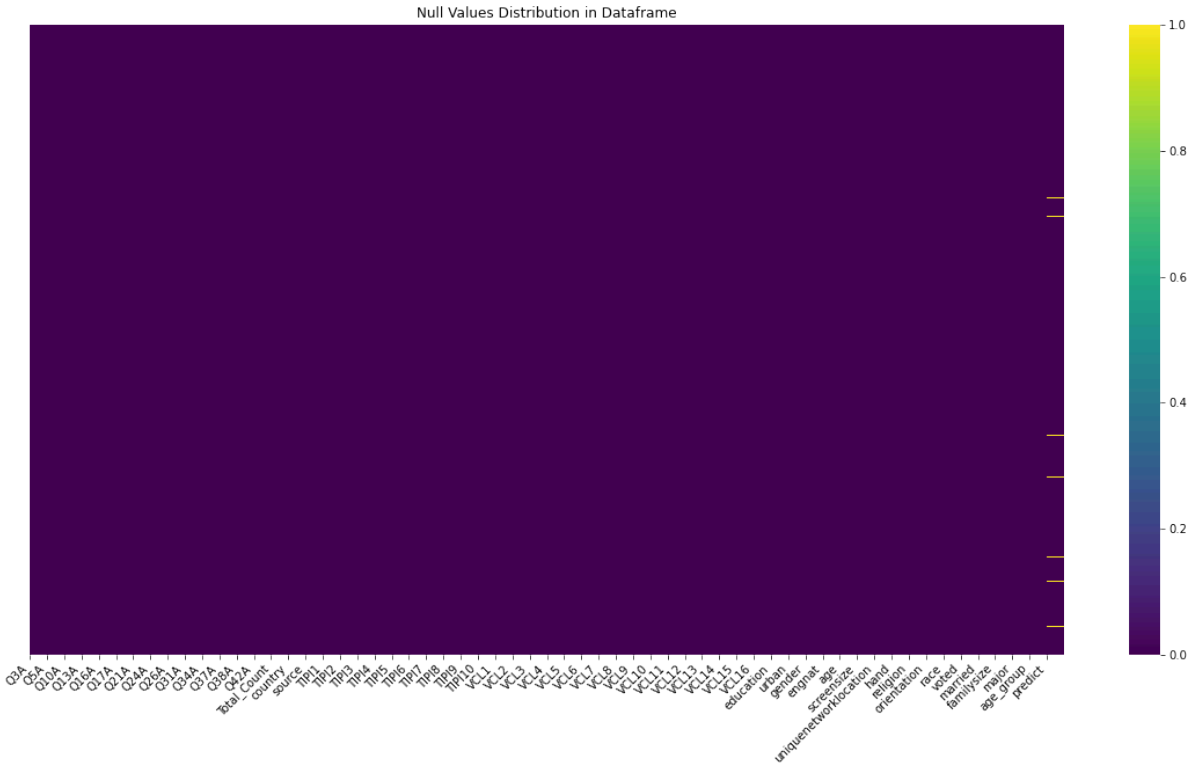
	Q3A	Q5A	Q10A	Q13A	Q16A	Q17A	Q21A	Q24A	Q26A	Q31A
0	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...
28346	False	False	False	False	False	False	False	False	False	False
28347	False	False	False	False	False	False	False	False	False	False
28348	False	False	False	False	False	False	False	False	False	False
28349	False	False	False	False	False	False	False	False	False	False
28350	False	False	False	False	False	False	False	False	False	False

	Q34A	Q37A	Q38A	Q42A	Total_Count	country	source	TIPI1	TIPI2
0	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...
28346	False	False	False	False	False	False	False	False	False
28347	False	False	False	False	False	False	False	False	False
28348	False	False	False	False	False	False	False	False	False
28349	False	False	False	False	False	False	False	False	False
28350	False	False	False	False	False	False	False	False	False

	TIPI3	TIPI4	TIPI5	TIPI6	TIPI7	TIPI8	TIPI9	TIPI10	VCL1	VCL2
0	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...
28346	False	False	False	False	False	False	False	False	False	False
28347	False	False	False	False	False	False	False	False	False	False
28348	False	False	False	False	False	False	False	False	False	False
28349	False	False	False	False	False	False	False	False	False	False
28350	False	False	False	False	False	False	False	False	False	False

	VCL3	VCL4	VCL5	VCL6	VCL7	VCL8	VCL9	VCL10	VCL11	VCL12
0	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...
28346	False	False	False	False	False	False	False	False	False	False
28347	False	False	False	False	False	False	False	False	False	False
28348	False	False	False	False	False	False	False	False	False	False
28349	False	False	False	False	False	False	False	False	False	False
28350	False	False	False	False	False	False	False	False	False	False

```
       VCL13  VCL14  VCL15  VCL16  education  urban  gender  engnat    age  \
0      False  False  False  False      False  False   False   False  False
1      False  False  False  False      False  False   False   False  False
2      False  False  False  False      False  False   False   False  False
3      False  False  False  False      False  False   False   False  False
4      False  False  False  False      False  False   False   False  False
...      ...    ...    ...    ...        ...    ...     ...     ...    ...
28346  False  False  False  False      False  False   False   False  False
28347  False  False  False  False      False  False   False   False  False
28348  False  False  False  False      False  False   False   False  False
28349  False  False  False  False      False  False   False   False  False
28350  False  False  False  False      False  False   False   False  False

       screensize  uniquenetworklocation   hand  religion  orientation   race
\
0           False                  False  False     False        False  False
1           False                  False  False     False        False  False
2           False                  False  False     False        False  False
3           False                  False  False     False        False  False
4           False                  False  False     False        False  False
...           ...                    ...    ...       ...          ...    ...
28346       False                  False  False     False        False  False
28347       False                  False  False     False        False  False
28348       False                  False  False     False        False  False
28349       False                  False  False     False        False  False
28350       False                  False  False     False        False  False

       voted  married  familysize  major  age_group  predict
0      False    False       False  False      False    False
1      False    False       False  False      False    False
2      False    False       False  False      False    False
3      False    False       False  False      False    False
4      False    False       False  False      False    False
...      ...      ...         ...    ...        ...      ...
28346  False    False       False  False      False    False
28347  False    False       False  False      False    False
28348  False    False       False  False      False    False
28349  False    False       False  False      False    False
28350  False    False       False  False      False    False

[28351 rows x 60 columns]
```



In [377]:
```
1 Depression.isna().sum()
```

Out[377]:

Q3A	0
Q5A	0
Q10A	0
Q13A	0
Q16A	0
Q17A	0
Q21A	0
Q24A	0
Q26A	0
Q31A	0
Q34A	0
Q37A	0
Q38A	0
Q42A	0
Total_Count	0
country	0
source	0
TIPI1	0
TIPI2	0

In [378]:
```
1 Anxiety.isna().sum()
```

Out[378]:
```
Q2A                     0
Q4A                     0
Q7A                     0
Q9A                     0
Q15A                    0
Q19A                    0
Q20A                    0
Q23A                    0
Q25A                    0
Q28A                    0
Q30A                    0
Q36A                    0
Q40A                    0
Q41A                    0
Total_Count             0
country                 0
source                  0
TIPI1                   0
TIPI2                   0
```

In [379]:
```
1 Stress.isna().sum()
```

Out[379]:
```
Q1A                     0
Q6A                     0
Q8A                     0
Q11A                    0
Q12A                    0
Q14A                    0
Q18A                    0
Q22A                    0
Q27A                    0
Q29A                    0
Q32A                    0
Q33A                    0
Q35A                    0
Q39A                    0
Total_Count             0
country                 0
source                  0
TIPI1                   0
TIPI2                   0
```

In [380]:
```
1 Depression=Depression.dropna()
```

In [381]:
```
1 Depression.isna().sum()
```

Out[381]:
```
Q3A                     0
Q5A                     0
Q10A                    0
Q13A                    0
Q16A                    0
Q17A                    0
Q21A                    0
Q24A                    0
Q26A                    0
Q31A                    0
Q34A                    0
Q37A                    0
Q38A                    0
Q42A                    0
Total_Count             0
country                 0
source                  0
TIPI1                   0
TIPI2                   0
```

In [382]:
```
1 depression.columns
```

Out[382]:
```
Index(['Q3A', 'Q5A', 'Q10A', 'Q13A', 'Q16A', 'Q17A', 'Q21A', 'Q24A', 'Q26A',
       'Q31A', 'Q34A', 'Q37A', 'Q38A', 'Q42A', 'Total_Count'],
      dtype='object')
```

In [383]:
```
1 Depression=Depression.drop(columns=['Total_Count','age', 'engnat', 'screen
2 Anxiety=Anxiety.drop(columns=['Total_Count','age', 'engnat', 'screensize',
3 Stress=Stress.drop(columns=['Total_Count','age', 'engnat', 'screensize', '
```

In [384]:
```
1 Depression.head()
```

Out[384]:

	Q3A	Q5A	Q10A	Q13A	Q16A	Q17A	Q21A	Q24A	Q26A	Q31A	Q34A	Q37A	Q38A	Q42A
0	1	2	2	0	1	2	0	0	1	2	3	1	0	1
1	2	3	2	3	2	3	2	1	3	2	3	2	2	2
2	1	3	3	1	3	1	3	2	1	3	2	3	3	2
3	0	2	0	0	0	0	0	0	1	0	0	0	0	1
4	2	2	2	3	3	2	2	2	3	3	3	3	2	3

In [385]:
```
1 Anxiety.head()
```

Out[385]:

	Q2A	Q4A	Q7A	Q9A	Q15A	Q19A	Q20A	Q23A	Q25A	Q28A	Q30A	Q36A	Q40A	Q41A
0	2	0	3	2	1	0	1	0	0	0	2	0	3	3
1	1	3	3	3	3	3	3	3	3	3	3	3	3	3
2	0	2	2	2	2	0	2	2	1	1	2	1	1	1
3	0	0	1	0	1	0	1	0	1	0	0	0	0	0
4	3	3	3	3	3	3	3	3	1	3	2	3	3	3

In [386]:
```
1 Stress.head()
```

Out[386]:

	Q1A	Q6A	Q8A	Q11A	Q12A	Q14A	Q18A	Q22A	Q27A	Q29A	Q32A	Q33A	Q35A	Q39A
0	1	2	1	1	0	3	0	0	3	2	0	1	0	2
1	1	1	3	1	3	3	3	2	1	1	3	3	2	2
2	0	0	2	0	1	1	1	0	0	1	1	3	1	3
3	0	1	0	1	0	1	1	0	1	0	0	0	0	1
4	3	3	3	3	3	2	3	3	1	3	1	3	1	1

2.1 Model for Anxiety

In [387]:
```
1 X=Depression[['Q3A', 'Q5A', 'Q10A', 'Q13A', 'Q16A', 'Q17A', 'Q21A', 'Q24A'
2        'Q31A', 'Q34A', 'Q37A', 'Q38A', 'Q42A', 'TIPI1', 'TIPI2', 'TIPI3',
```

In [388]:
```
1 y=Depression[['predict']].values
2 y = y.flatten()
```

In [389]:
```
1 X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.35,random_s
2 X_train_scaled = scaler.fit_transform(X_train)
3 X_test_scaled = scaler.transform(X_test)
```

In [390]:
```
1 print('Training Set:',X_train.shape,y_train.shape)
2 print('Test Set:',X_test.shape,y_test.shape)
```

```
Training Set: (18040, 33) (18040,)
Test Set: (9714, 33) (9714,)
```

In [391]:

```
clf = LazyClassifier(verbose=0,ignore_warnings=True, custom_metric=None)
models,predictions = clf.fit(X_train, X_test, y_train, y_test)

print(models)
```

```
 97%|████████████████████████████████████████████████████████████████████████
███████    | 28/29 [09:32<00:07,  7.02s/it]

[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of tes
ting was 0.005769 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 217
[LightGBM] [Info] Number of data points in the train set: 18040, number of us
ed features: 33
[LightGBM] [Info] Start training from score -1.244895
[LightGBM] [Info] Start training from score -2.233001
[LightGBM] [Info] Start training from score -1.656539
[LightGBM] [Info] Start training from score -1.374392
[LightGBM] [Info] Start training from score -1.826158

100%|████████████████████████████████████████████████████████████████████████
██████████| 29/29 [09:37<00:00, 19.91s/it]
```

Model	Accuracy	Balanced Accuracy	ROC AUC	F1 Score
LogisticRegression	1.00	1.00	None	1.00
SVC	0.99	0.98	None	0.99
NuSVC	0.98	0.97	None	0.98
QuadraticDiscriminantAnalysis	0.95	0.95	None	0.95
LinearDiscriminantAnalysis	0.94	0.94	None	0.94
LGBMClassifier	0.95	0.93	None	0.95
ExtraTreesClassifier	0.93	0.90	None	0.93
RandomForestClassifier	0.92	0.88	None	0.92
GaussianNB	0.87	0.87	None	0.88
NearestCentroid	0.86	0.86	None	0.86
BaggingClassifier	0.85	0.81	None	0.85
KNeighborsClassifier	0.82	0.76	None	0.81
AdaBoostClassifier	0.73	0.73	None	0.73
DecisionTreeClassifier	0.77	0.72	None	0.77
BernoulliNB	0.78	0.72	None	0.78
LabelPropagation	0.76	0.70	None	0.76
LabelSpreading	0.76	0.70	None	0.76
ExtraTreeClassifier	0.75	0.70	None	0.75
LinearSVC	0.79	0.68	None	0.76
CalibratedClassifierCV	0.79	0.68	None	0.76
SGDClassifier	0.73	0.64	None	0.73
Perceptron	0.73	0.64	None	0.73
PassiveAggressiveClassifier	0.73	0.63	None	0.72
RidgeClassifier	0.59	0.46	None	0.48
RidgeClassifierCV	0.59	0.46	None	0.48
DummyClassifier	0.29	0.20	None	0.13

Model	Time Taken
LogisticRegression	3.05
SVC	28.12
NuSVC	136.14
QuadraticDiscriminantAnalysis	0.61
LinearDiscriminantAnalysis	1.93
LGBMClassifier	4.43
ExtraTreesClassifier	5.98
RandomForestClassifier	5.89
GaussianNB	0.46
NearestCentroid	0.48
BaggingClassifier	2.91
KNeighborsClassifier	9.52
AdaBoostClassifier	5.77
DecisionTreeClassifier	0.68
BernoulliNB	0.50
LabelPropagation	145.38
LabelSpreading	112.09
ExtraTreeClassifier	0.50
LinearSVC	23.10
CalibratedClassifierCV	83.66
SGDClassifier	1.59
Perceptron	0.76
PassiveAggressiveClassifier	0.93
RidgeClassifier	0.57

```
RidgeClassifierCV                   0.53
DummyClassifier                     0.25
```

Algorithm (1): K Nearest Neighbors

In [392]:
```
knn_depression = KNeighborsClassifier(n_neighbors=15).fit(X_train_scaled,y
```

In [393]:
```
accuracy_knn = round(accuracy_score(y_test,knn_depression.predict(X_test_s
precision_knn = round(precision_score(y_test,knn_depression.predict(X_test
recall_knn = round(recall_score(y_test,knn_depression.predict(X_test_scale
f1_score_knn = round(f1_score(y_test,knn_depression.predict(X_test_scaled)
cross_validation_knn = round(np.mean(cross_val_score(knn_depression, X_tra
```

In [394]:
```
print('Accuracy:', accuracy_knn)
print('Precision:', precision_knn)
print('Recall:', recall_knn)
print('F1_Score:', f1_score_knn)
print('Cross Validation:', cross_validation_knn)
```

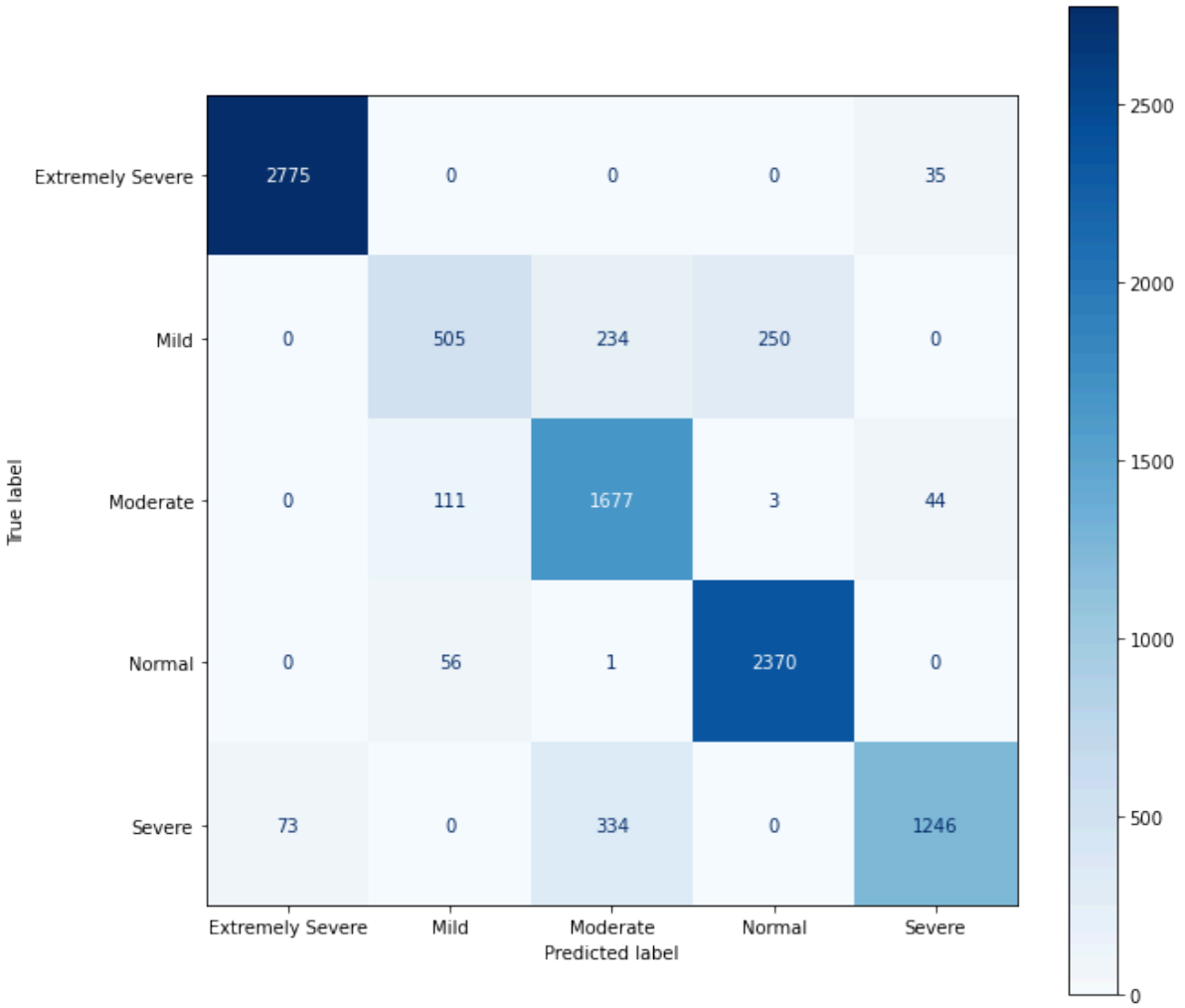
```
Accuracy: 0.883
Precision: 0.885
Recall: 0.883
F1_Score: 0.878
Cross Validation: 0.88
```

In [395]:
```
classification = classification_report(digits=4, y_true=y_test, y_pred=knn
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     0.9744    0.9875    0.9809      2810
            Mild     0.7515    0.5106    0.6081       989
        Moderate     0.7467    0.9139    0.8219      1835
          Normal     0.9035    0.9765    0.9386      2427
          Severe     0.9404    0.7538    0.8368      1653

        accuracy                         0.8825      9714
       macro avg     0.8633    0.8285    0.8373      9714
    weighted avg     0.8852    0.8825    0.8778      9714
```

In [396]:
```
1 fig, ax = plt.subplots(figsize=(10, 10))
2 plot_confusion_matrix(knn_depression, X_test_scaled, y_test, ax=ax, cmap='
```

Out[396]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14bbf6d2b
50>
```



Algorithm (2): Decision Tree

In [397]:
```
1 decision_tree_depression = DecisionTreeClassifier(criterion='entropy',spli
```

In [398]:
```
1 accuracy_dt = round(accuracy_score(y_test,decision_tree_depression.predict
2 precision_dt = round(precision_score(y_test,decision_tree_depression.predi
3 recall_dt = round(recall_score(y_test,decision_tree_depression.predict(X_t
4 f1_score_dt = round(f1_score(y_test,decision_tree_depression.predict(X_tes
5 cross_validation_dt = round(np.mean(cross_val_score(decision_tree_depressi
```

In [399]:
```
print('Accuracy:', accuracy_dt)
print('Precision:', precision_dt)
print('Recall:', recall_dt)
print('F1_Score:', f1_score_dt)
print('Cross Validation:', cross_validation_dt)
```

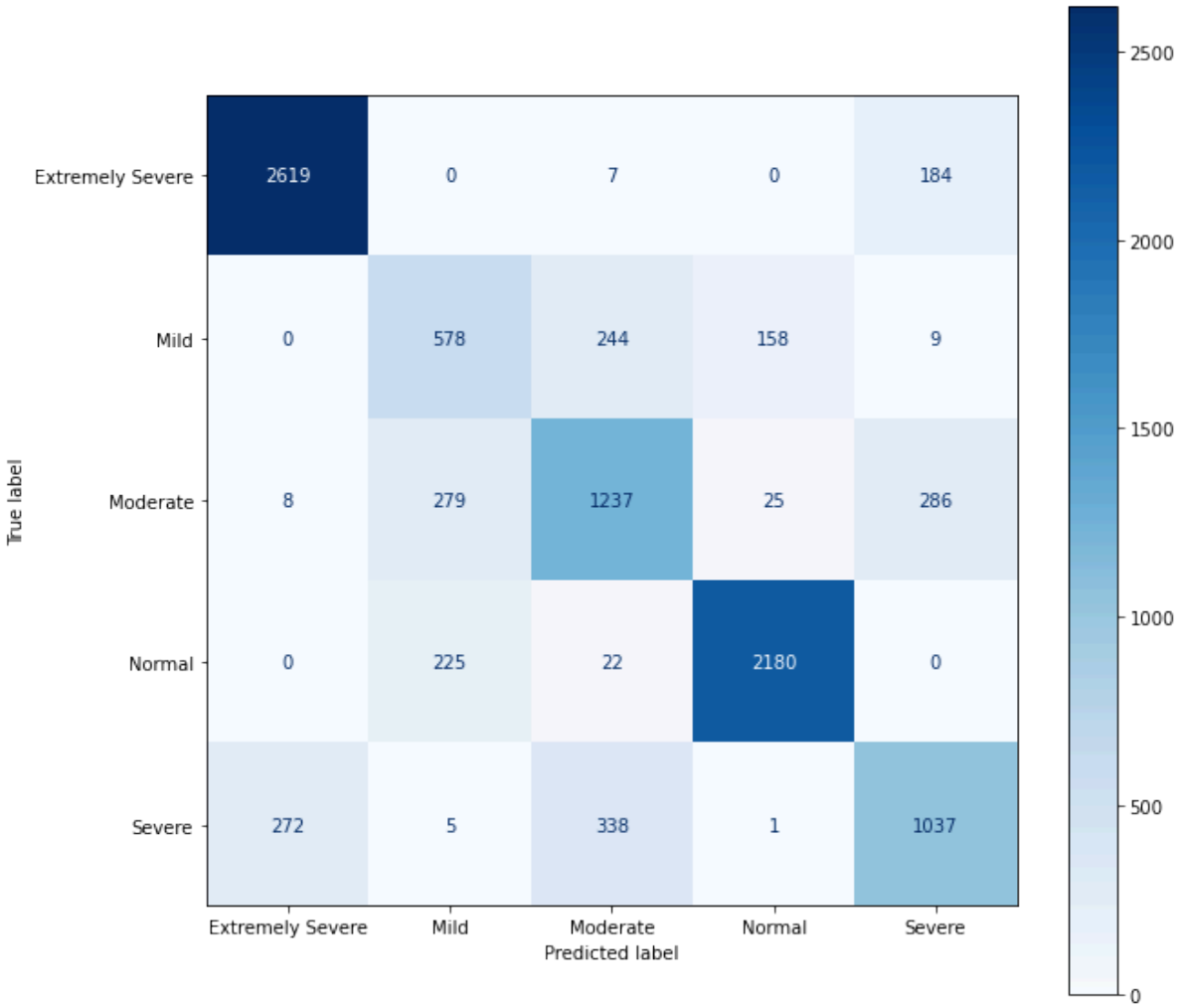
```
Accuracy: 0.788
Precision: 0.789
Recall: 0.788
F1_Score: 0.788
Cross Validation: 0.787
```

In [400]:
```
classification = classification_report(digits=4, y_true=y_test, y_pred=dec
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     0.9034    0.9320    0.9175      2810
            Mild     0.5317    0.5844    0.5568       989
        Moderate     0.6694    0.6741    0.6717      1835
          Normal     0.9222    0.8982    0.9100      2427
          Severe     0.6840    0.6273    0.6545      1653

        accuracy                         0.7876      9714
       macro avg     0.7421    0.7432    0.7421      9714
    weighted avg     0.7887    0.7876    0.7877      9714
```

In [401]:
```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(decision_tree_depression, X_test_scaled, y_test, ax=
```

Out[401]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14bc1886b
e0>
```



Algorithm (3): Random Forest

In [402]:
```
random_forest_depression = RandomForestClassifier(n_estimators=200, min_sa
```

In [403]:
```
accuracy_rf = round(accuracy_score(y_test, random_forest_depression.predic
precision_rf = round(precision_score(y_test, random_forest_depression.pred
recall_rf = round(recall_score(y_test, random_forest_depression.predict(X_
f1_Score_rf = round(f1_score(y_test, random_forest_depression.predict(X_te
cross_validation_rf = round(np.mean(cross_val_score(random_forest_depressi
```

In [404]:
```
print('Accuracy:', accuracy_rf)
print('Precision:', precision_rf)
print('Recall:', recall_rf)
print('F1_Score:', f1_Score_rf)
print('Cross Validation:', cross_validation_rf)
```

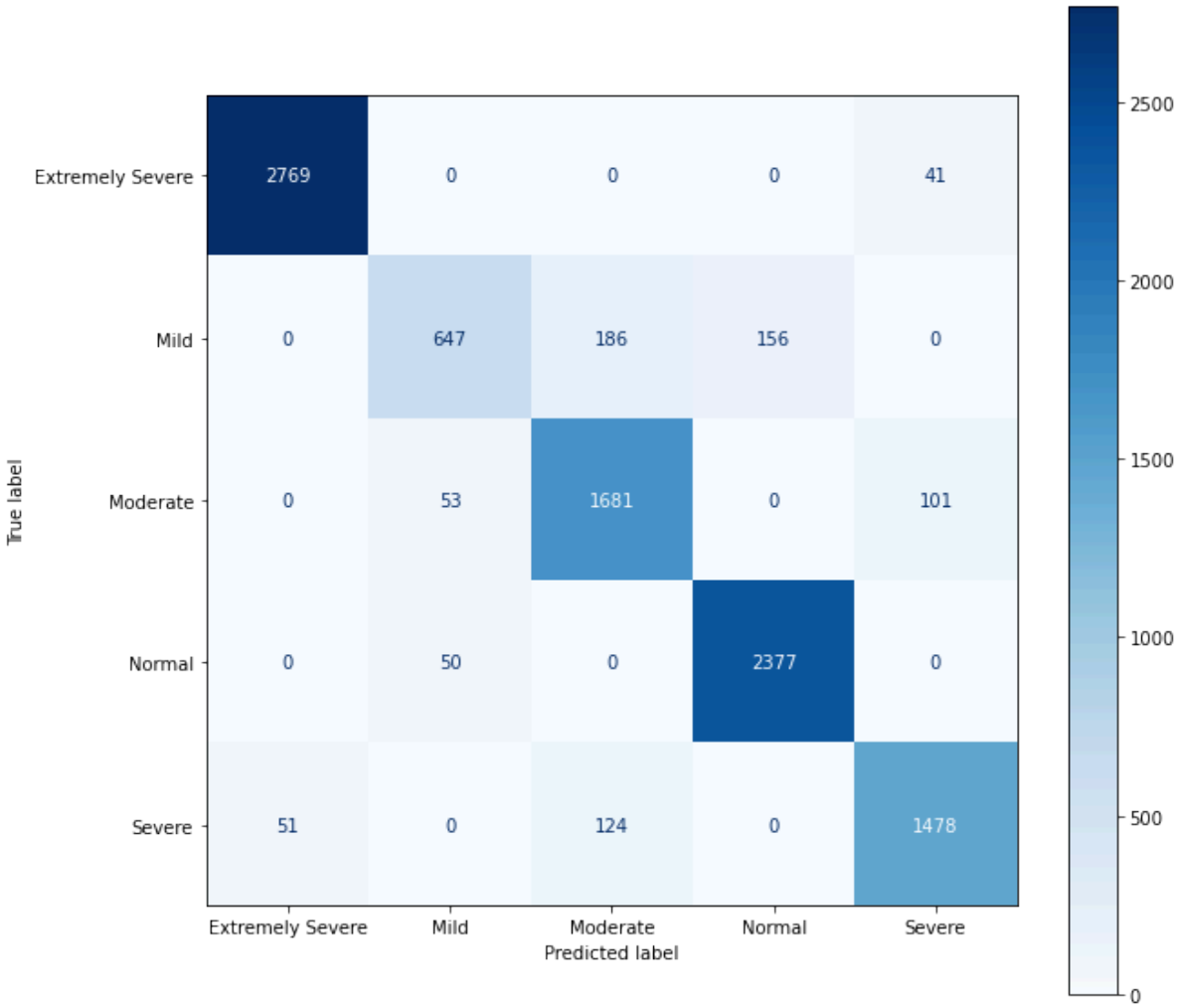
```
Accuracy: 0.922
Precision: 0.921
Recall: 0.922
F1_Score: 0.919
Cross Validation: 0.924
```

In [405]:
```
classification=classification_report(digits=4, y_true=y_test, y_pred=rando
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     0.9819    0.9854    0.9837      2810
            Mild     0.8627    0.6542    0.7441       989
        Moderate     0.8443    0.9161    0.8787      1835
          Normal     0.9384    0.9794    0.9585      2427
          Severe     0.9123    0.8941    0.9031      1653

        accuracy                         0.9216      9714
       macro avg     0.9079    0.8858    0.8936      9714
    weighted avg     0.9211    0.9216    0.9195      9714
```

In [406]:
```
1 fig, ax = plt.subplots(figsize=(10, 10))
2 plot_confusion_matrix(random_forest_depression,X_test_scaled,y_test,ax=ax,
```

Out[406]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14bc0d357
c0>
```



Algorithm (4): Naive Bayes

In [407]:
```
1 gaussian_nb_depression = GaussianNB().fit(X_train_scaled, y_train)
```

In [408]:
```
1 accuracy_nb = round(accuracy_score(y_test, gaussian_nb_depression.predict(
2 precision_nb = round(precision_score(y_test, gaussian_nb_depression.predic
3 recall_nb = round(recall_score(y_test, gaussian_nb_depression.predict(X_te
4 f1_score_nb = round(f1_score(y_test, gaussian_nb_depression.predict(X_test
5 cross_validation_nb = round(np.mean(cross_val_score(gaussian_nb_depression
```

In [409]:

```
print('Accuracy:', accuracy_nb)
print('Precision:', precision_nb)
print('Recall', recall_nb)
print('F1_Score:', f1_score_nb)
print('Cross Validation:', cross_validation_nb)
```

```
Accuracy: 0.872
Precision: 0.895
Recall 0.872
F1_Score: 0.878
Cross Validation: 0.873
```

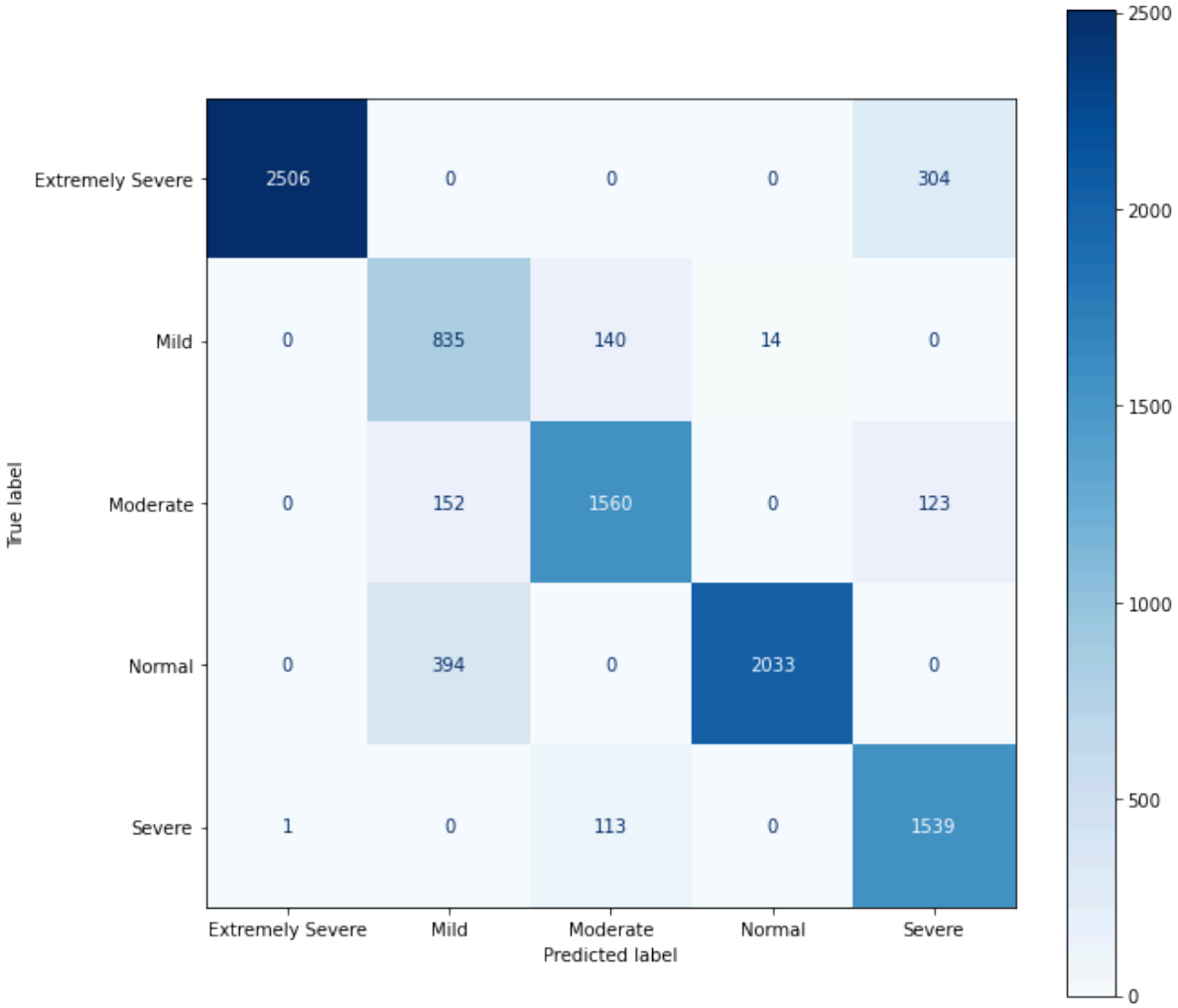
In [410]:

```
classification=classification_report(digits=4, y_true=y_test, y_pred=gauss
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     0.9996    0.8918    0.9426      2810
            Mild     0.6046    0.8443    0.7046       989
        Moderate     0.8605    0.8501    0.8553      1835
          Normal     0.9932    0.8377    0.9088      2427
          Severe     0.7828    0.9310    0.8505      1653

        accuracy                         0.8722      9714
       macro avg     0.8481    0.8710    0.8524      9714
    weighted avg     0.8946    0.8722    0.8778      9714
```

In [411]:
```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(gaussian_nb_depression, X_test_scaled, y_test,ax=ax,
```

Out[411]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14bbeea0a
90>
```



Algorithm (5): Logistic Regression

In [412]:
```
logistic_regression_depression = LogisticRegression().fit(X_train_scaled,
```

In [413]:
```
accuracy_lr = round(accuracy_score(y_test, logistic_regression_depression.
precision_lr = round(precision_score(y_test, logistic_regression_depressio
recall_lr = round(recall_score(y_test, logistic_regression_depression.pred
f1_score_lr = round(f1_score(y_test, logistic_regression_depression.predic
cross_validation_lr = round(np.mean(cross_val_score(logistic_regression_de
```

In [414]:

```
print('Accuracy:', accuracy_lr)
print('F1_Score:', f1_score_lr)
print('Recall:', recall_lr)
print('Precision:', precision_lr)
print('Cross Validation:', cross_validation_lr)
```

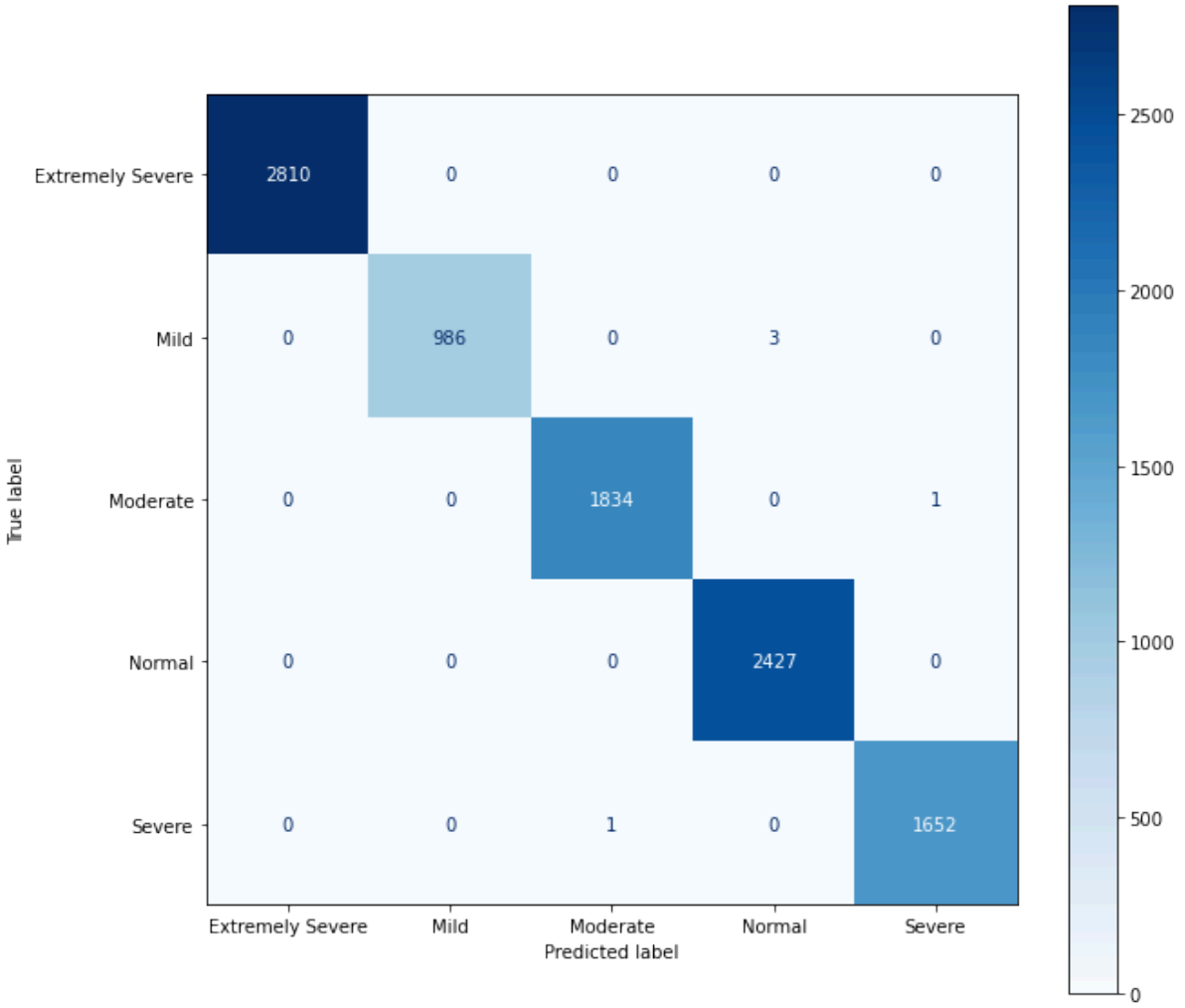
```
Accuracy: 0.999
F1_Score: 0.999
Recall: 0.999
Precision: 0.999
Cross Validation: 0.998
```

In [415]:

```
classification = classification_report(digits=4, y_true=y_test, y_pred=log
print(classification)
```

	precision	recall	f1-score	support
Extremely Severe	1.0000	1.0000	1.0000	2810
Mild	1.0000	0.9970	0.9985	989
Moderate	0.9995	0.9995	0.9995	1835
Normal	0.9988	1.0000	0.9994	2427
Severe	0.9994	0.9994	0.9994	1653
accuracy			0.9995	9714
macro avg	0.9995	0.9992	0.9993	9714
weighted avg	0.9995	0.9995	0.9995	9714

In [416]:
```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(logistic_regression_depression, X_test_scaled, y_tes
plt.show()
```



Algorithm (5): Supprt Vector Classifier

In [417]:
```
svm_depression = SVC(C=100, gamma=0.1, kernel='rbf').fit(X_train_scaled,y_
```

In [418]:
```
accuracy_svm = round(accuracy_score(y_test, svm_depression.predict(X_test_
precision_svm = round(precision_score(y_test, svm_depression.predict(X_tes
recall_svm = round(recall_score(y_test, svm_depression.predict(X_test_scal
f1_score_svm = round(f1_score(y_test, svm_depression.predict(X_test_scaled
cross_validation_svm = round(np.mean(cross_val_score(svm_depression, X_tra
```

In [419]:
```
print('Accuracy:', accuracy_svm)
print('F1_Score:', f1_score_svm)
print('Recall_Score:', recall_svm)
print('Precision_Score:', precision_svm)
print('Cross Validation Score:', cross_validation_svm)
```

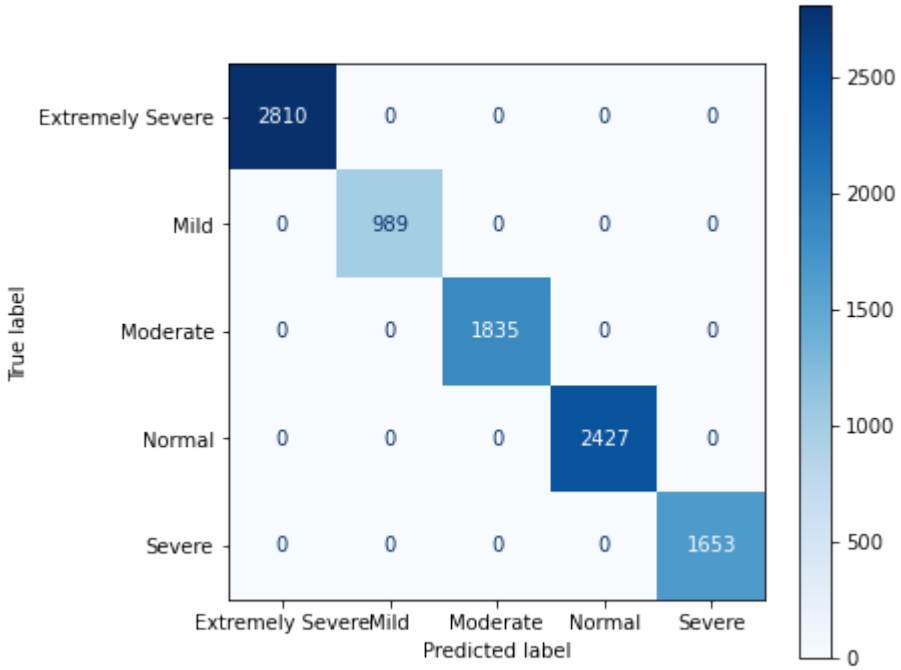
```
Accuracy: 1.0
F1_Score: 1.0
Recall_Score: 1.0
Precision_Score: 1.0
Cross Validation Score: 1.0
```

In [420]:
```
classification=classification_report(digits=4, y_true=y_test, y_pred=svm_d
print(classification)
```

	precision	recall	f1-score	support
Extremely Severe	1.0000	1.0000	1.0000	2810
Mild	1.0000	1.0000	1.0000	989
Moderate	1.0000	1.0000	1.0000	1835
Normal	1.0000	1.0000	1.0000	2427
Severe	1.0000	1.0000	1.0000	1653
accuracy			1.0000	9714
macro avg	1.0000	1.0000	1.0000	9714
weighted avg	1.0000	1.0000	1.0000	9714

In [421]:
```
fig, ax = plt.subplots(figsize=(6, 6))
plot_confusion_matrix(svm_depression, X_test_scaled, y_test,ax=ax, cmap='B
```

Out[421]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14bb7815a
90>
```



In [422]:
```
Result={'Model':['Random_Forest', 'Decision_Tree', 'Naive_Baise', 'K_Neare
        'Accuracy(%)':[accuracy_rf*100, accuracy_dt*100, accuracy_nb*100,
        'Precision(%)':[precision_rf*100, precision_dt*100, precision_nb*1
        'Recall(%)':[recall_rf*100, recall_dt*100, recall_nb*100, recall_k
        'F1_Score(%)':[f1_Score_rf*100, f1_score_dt*100, f1_score_nb*100,
```

In [423]:
```
Result_Depression=pd.DataFrame(Result)
Result_Depression.to_csv('/Result_Depression.csv', index=False)
```

In [424]:
```
Result_Depression
```

Out[424]:

	Model	Accuracy(%)	Precision(%)	Recall(%)	F1_Score(%)
0	Random_Forest	92.20	92.10	92.20	91.90
1	Decision_Tree	78.80	78.90	78.80	78.80
2	Naive_Baise	87.20	89.50	87.20	87.80
3	K_Nearest_Neighbors	88.30	88.50	88.30	87.80
4	Logistic_Regression	99.90	99.90	99.90	99.90
5	SVM	100.00	100.00	100.00	100.00

Test by My Self

In [425]:
```
Depression
```

Out[425]:

	Q3A	Q5A	Q10A	Q13A	Q16A	Q17A	Q21A	Q24A	Q26A	Q31A	Q34A	Q37A	Q38A	Q
0	1	2	2	0	1	2	0	0	1	2	3	1	0	
1	2	3	2	3	2	3	2	1	3	2	3	2	2	
2	1	3	3	1	3	1	3	2	1	3	2	3	3	
3	0	2	0	0	0	0	0	0	1	0	0	0	0	
4	2	2	2	3	3	2	2	2	3	3	3	3	2	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
28346	0	1	0	1	1	0	0	1	1	0	0	0	0	
28347	2	2	3	3	3	2	3	3	3	3	3	2	3	
28348	1	0	0	1	0	0	0	1	0	1	0	0	0	
28349	1	2	0	3	0	1	1	1	2	1	1	0	1	
28350	1	3	0	2	3	3	3	1	1	1	2	1	3	

27754 rows × 34 columns

In [426]:
```
1 Depression[Depression['predict'] == 'Mild']
```

Out[426]:

	Q3A	Q5A	Q10A	Q13A	Q16A	Q17A	Q21A	Q24A	Q26A	Q31A	Q34A	Q37A	Q38A	C
9	1	0	0	2	0	2	0	1	3	0	0	0	0	
22	0	2	1	1	1	0	1	1	1	3	0	0	1	
27	0	1	0	1	1	0	1	1	0	1	1	0	0	
31	1	1	2	1	1	1	0	1	0	1	0	1	0	
61	1	3	0	1	0	0	1	0	1	0	0	1	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
28308	0	1	1	2	0	1	1	1	1	1	1	0	1	
28324	1	0	0	0	2	0	0	1	1	2	0	2	0	
28338	1	1	1	2	0	2	0	0	1	1	2	1	0	
28340	0	1	0	2	1	1	0	0	3	2	0	0	0	
28342	0	1	1	1	1	0	1	1	1	1	0	1	1	

2923 rows × 34 columns

In [427]:
```
1 Depression.columns
```

Out[427]:
```
Index(['Q3A', 'Q5A', 'Q10A', 'Q13A', 'Q16A', 'Q17A', 'Q21A', 'Q24A', 'Q26A',
       'Q31A', 'Q34A', 'Q37A', 'Q38A', 'Q42A', 'TIPI1', 'TIPI2', 'TIPI3',
       'TIPI4', 'TIPI5', 'TIPI6', 'TIPI7', 'TIPI8', 'TIPI9', 'TIPI10',
       'education', 'urban', 'gender', 'religion', 'orientation', 'race',
       'married', 'familysize', 'age_group', 'predict'],
      dtype='object')
```

In [428]:
```
1 input_data_Moderate = [1, 2, 2, 0, 1, 2, 0, 0, 1, 2, 3, 1, 0, 1, 1, 1, 7,
2 input_data_scaled = scaler.transform([input_data_Moderate])
```

In [429]:
```
1 prediction = svm_depression.predict(input_data_scaled)
2 print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [430]:
```
1 input_data_Mild = [1, 0, 0, 2, 0, 2, 0, 1, 3, 0, 0, 0, 0, 2, 1, 7, 5, 7, 1
2 input_data_scaled = scaler.transform([input_data_Mild])
```

In [431]:
```
1 prediction = svm_depression.predict(input_data_scaled)
2 print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [432]:
```
input_data_Extremely_Severe = [2, 2, 3, 3, 3, 2, 3, 3, 3, 3, 3, 2, 3, 3, 4
input_data_scaled = scaler.transform([input_data_Extremely_Severe])
```

In [433]:
```
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [434]:
```
input_data_Normal = [0, 2, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 7, 6, 4, 5,
input_data_scaled = scaler.transform([input_data_Normal])
```

In [435]:
```
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Normal
```

In [436]:
```
input_data_Severe = [1, 3, 0, 2, 3, 3, 3, 1, 1, 1, 2, 1, 3, 3, 6, 2, 3, 5,
input_data_scaled = scaler.transform([input_data_Severe])
```

In [437]:
```
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [438]:

```
column_scales = {
    'Q3A': list(range(4)),
    'Q5A': list(range(4)),
    'Q10A': list(range(4)),
    'Q13A': list(range(4)),
    'Q16A': list(range(4)),
    'Q17A': list(range(4)),
    'Q21A': list(range(4)),
    'Q24A': list(range(4)),
    'Q26A': list(range(4)),
    'Q31A': list(range(4)),
    'Q34A': list(range(4)),
    'Q37A': list(range(4)),
    'Q38A': list(range(4)),
    'Q42A': list(range(4)),
    'TIPI1': list(range(1, 8)),
    'TIPI2': list(range(1, 8)),
    'TIPI3': list(range(1, 8)),
    'TIPI4': list(range(1, 8)),
    'TIPI5': list(range(1, 8)),
    'TIPI6': list(range(1, 8)),
    'TIPI7': list(range(1, 8)),
    'TIPI8': list(range(1, 8)),
    'TIPI9': list(range(1, 8)),
    'TIPI10': list(range(1, 8)),
    'education': list(range(1, 5)),
    'urban': list(range(1, 4)),
    'gender': list(range(1, 4)),
    'religion': list(range(1, 13)),
    'orientation': list(range(1, 6)),
    'race': [10, 20, 30, 40, 50, 60, 70],
    'married': list(range(1, 4)),
    'familysize': list(range(1, 101)),
    'age_group': list(range(1, 7))
}
```

In [439]:

```
random_lists = []
for i in range(30):
    random_list = [
        random.choice(column_scales[column]) for column in [
            'Q3A', 'Q5A', 'Q10A', 'Q13A', 'Q16A', 'Q17A', 'Q21A', 'Q24A',
       'Q31A', 'Q34A', 'Q37A', 'Q38A', 'Q42A', 'TIPI1', 'TIPI2', 'TIPI3',
            'TIPI4', 'TIPI5', 'TIPI6', 'TIPI7', 'TIPI8', 'TIPI9', 'TIPI10'
            'education', 'urban', 'gender', 'religion', 'orientation', 'ra
            'married', 'familysize', 'age_group'
        ]
    ]
    random_lists.append(random_list)
```

In [440]:

```
for i, random_list in enumerate(random_lists, start=1):
    print(f"random_values{i} = {random_list}")
```

```
random_values1 = [3, 1, 1, 3, 0, 1, 1, 1, 0, 2, 2, 3, 1, 0, 4, 7, 2, 6, 3, 2,
3, 5, 7, 4, 2, 1, 3, 11, 4, 40, 3, 27, 2]
random_values2 = [0, 0, 2, 3, 0, 2, 3, 2, 0, 0, 0, 1, 3, 1, 3, 3, 4, 3, 6, 7,
6, 3, 5, 4, 2, 3, 3, 4, 5, 50, 1, 93, 5]
random_values3 = [0, 2, 1, 0, 0, 3, 1, 1, 2, 1, 0, 3, 2, 1, 5, 1, 3, 6, 6, 6,
2, 1, 6, 3, 2, 2, 3, 11, 5, 60, 3, 21, 6]
random_values4 = [0, 0, 3, 1, 0, 3, 1, 2, 0, 2, 2, 0, 2, 1, 6, 6, 3, 1, 4, 7,
5, 2, 1, 3, 1, 1, 3, 4, 3, 40, 1, 36, 3]
random_values5 = [1, 0, 3, 3, 0, 3, 2, 3, 0, 3, 3, 0, 2, 0, 5, 4, 7, 4, 6, 2,
1, 4, 6, 5, 2, 1, 3, 6, 3, 30, 3, 92, 6]
random_values6 = [0, 0, 1, 3, 2, 0, 1, 3, 3, 0, 1, 0, 1, 1, 7, 6, 3, 7, 1, 1,
4, 1, 7, 1, 4, 1, 1, 5, 2, 40, 3, 94, 5]
random_values7 = [0, 3, 1, 1, 2, 3, 2, 2, 0, 3, 3, 2, 2, 1, 5, 6, 6, 3, 2, 7,
3, 3, 4, 5, 3, 3, 3, 2, 1, 10, 2, 67, 4]
random_values8 = [3, 1, 2, 1, 3, 2, 1, 0, 2, 3, 0, 3, 0, 0, 6, 4, 4, 7, 1, 4,
5, 2, 3, 1, 3, 1, 3, 5, 2, 10, 2, 68, 2]
random_values9 = [2, 1, 1, 2, 3, 1, 3, 1, 1, 2, 3, 1, 2, 3, 2, 7, 4, 6, 3, 7,
4, 6, 1, 6, 1, 2, 1, 8, 3, 70, 1, 59, 3]
random_values10 = [0, 3, 0, 1, 2, 0, 2, 2, 1, 3, 3, 2, 0, 3, 2, 4, 5, 1, 4,
4, 1, 7, 6, 5, 3, 1, 2, 9, 5, 10, 3, 25, 2]
random_values11 = [0, 2, 3, 1, 0, 1, 2, 0, 1, 2, 1, 0, 3, 0, 3, 6, 3, 7, 2,
7, 1, 3, 3, 2, 3, 3, 3, 6, 1, 10, 1, 90, 4]
random_values12 = [1, 0, 1, 3, 3, 3, 0, 1, 2, 3, 2, 1, 2, 0, 6, 1, 5, 4, 1,
5, 1, 5, 4, 3, 2, 1, 1, 9, 2, 60, 1, 56, 5]
random_values13 = [3, 2, 3, 3, 3, 2, 1, 1, 1, 0, 0, 2, 3, 0, 2, 6, 5, 2, 6,
6, 4, 4, 2, 3, 4, 1, 1, 8, 4, 60, 1, 12, 3]
random_values14 = [0, 1, 3, 0, 1, 3, 0, 0, 0, 0, 3, 0, 3, 2, 2, 7, 2, 2, 1,
6, 2, 6, 1, 2, 1, 2, 3, 4, 1, 40, 3, 77, 3]
random_values15 = [0, 1, 2, 1, 0, 0, 1, 0, 0, 3, 1, 2, 2, 0, 7, 4, 7, 2, 7,
2, 4, 3, 6, 6, 1, 1, 2, 10, 5, 50, 3, 13, 2]
random_values16 = [0, 1, 0, 0, 3, 2, 0, 0, 0, 2, 0, 1, 0, 0, 2, 5, 1, 6, 3,
6, 3, 4, 5, 3, 3, 1, 3, 6, 2, 30, 3, 77, 6]
random_values17 = [0, 0, 3, 2, 1, 1, 0, 1, 0, 3, 0, 2, 0, 2, 3, 1, 2, 6, 3,
4, 5, 6, 2, 5, 1, 3, 1, 3, 4, 70, 2, 31, 4]
random_values18 = [1, 3, 2, 0, 0, 2, 2, 3, 2, 0, 2, 2, 1, 0, 5, 7, 1, 6, 4,
5, 7, 7, 1, 1, 3, 1, 1, 12, 5, 60, 1, 92, 1]
random_values19 = [0, 1, 2, 3, 3, 2, 2, 2, 3, 3, 3, 1, 0, 3, 3, 7, 4, 2, 3,
3, 4, 2, 6, 1, 2, 1, 1, 4, 5, 60, 1, 13, 5]
random_values20 = [2, 2, 2, 2, 2, 1, 1, 2, 3, 2, 1, 1, 2, 2, 6, 2, 1, 2, 4,
3, 4, 3, 1, 1, 4, 2, 2, 1, 1, 20, 2, 95, 4]
random_values21 = [1, 2, 2, 0, 3, 1, 0, 0, 0, 0, 3, 0, 3, 1, 7, 1, 6, 4, 1,
3, 1, 3, 3, 7, 3, 2, 3, 11, 5, 50, 2, 30, 6]
random_values22 = [2, 1, 1, 1, 1, 3, 2, 1, 2, 0, 0, 0, 1, 0, 4, 5, 4, 5, 5,
7, 5, 7, 4, 1, 2, 2, 3, 6, 3, 60, 2, 12, 2]
random_values23 = [2, 2, 2, 0, 1, 2, 3, 1, 0, 2, 3, 3, 1, 1, 2, 2, 5, 5, 6,
4, 4, 1, 2, 6, 1, 1, 2, 5, 3, 30, 3, 99, 1]
random_values24 = [0, 3, 3, 0, 2, 3, 3, 3, 3, 0, 2, 0, 0, 1, 7, 5, 5, 7, 6,
4, 4, 7, 1, 1, 4, 3, 3, 11, 1, 30, 1, 38, 1]
random_values25 = [1, 2, 3, 1, 0, 0, 3, 1, 0, 1, 1, 2, 3, 0, 5, 3, 1, 3, 2,
1, 7, 3, 4, 3, 4, 3, 2, 6, 2, 50, 1, 44, 1]
random_values26 = [2, 2, 2, 1, 2, 2, 2, 1, 2, 2, 0, 0, 3, 1, 2, 5, 6, 1, 2,
6, 1, 1, 6, 7, 1, 2, 3, 8, 3, 20, 1, 14, 1]
random_values27 = [0, 2, 2, 3, 1, 3, 1, 2, 2, 2, 3, 3, 3, 1, 7, 6, 1, 1, 4,
3, 3, 1, 2, 4, 3, 2, 1, 8, 4, 20, 3, 100, 4]
random_values28 = [3, 0, 1, 3, 1, 3, 1, 2, 3, 0, 1, 1, 1, 0, 3, 4, 3, 5, 6,
7, 1, 1, 7, 1, 1, 2, 3, 8, 1, 10, 2, 53, 2]
random_values29 = [2, 1, 2, 2, 2, 2, 1, 2, 3, 2, 2, 3, 0, 2, 1, 4, 1, 4, 6,
```

```
4, 6, 7, 7, 7, 4, 3, 3, 6, 5, 10, 3, 26, 1]
random_values30 = [1, 0, 1, 2, 1, 1, 2, 3, 2, 1, 1, 0, 3, 0, 3, 3, 4, 3, 4,
2, 6, 4, 5, 6, 1, 1, 3, 12, 4, 30, 2, 87, 5]
```

In [441]:

```
random_values1 = [0, 0, 3, 0, 0, 0, 3, 0, 0, 0, 0, 0, 2, 1, 2, 3, 3, 4, 7,
random_values2 = [1, 0, 0, 0, 1, 2, 0, 3, 1, 0, 2, 3, 1, 0, 5, 3, 2, 4, 7,
random_values3 = [3, 0, 0, 1, 3, 0, 2, 1, 3, 2, 0, 1, 3, 2, 3, 5, 2, 7, 4,
random_values4 = [0, 0, 1, 0, 0, 3, 1, 2, 0, 1, 3, 2, 0, 1, 7, 1, 5, 3, 6,
random_values5 = [0, 1, 3, 0, 0, 3, 1, 0, 2, 1, 3, 0, 2, 3, 2, 6, 4, 5, 1,
random_values6 = [2, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 2, 4, 1, 6, 3, 5,
random_values7 = [3, 0, 0, 1, 3, 2, 0, 1, 3, 0, 2, 1, 3, 0, 6, 5, 2, 7, 4,
random_values8 = [0, 3, 1, 0, 0, 1, 3, 0, 0, 2, 1, 3, 2, 1, 2, 7, 1, 5, 3,
random_values9 = [2, 1, 3, 0, 0, 2, 3, 1, 0, 2, 1, 3, 0, 2, 1, 3, 2, 1, 4,
random_values10 = [1, 2, 0, 3, 1, 0, 2, 3, 1, 0, 0, 3, 1, 2, 6, 4, 1, 3, 5
random_values11 = [1, 0, 2,0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 2, 3, 5, 2, 7, 4,
random_values12 = [0, 3, 1, 2, 0, 3, 1, 0, 0, 1, 3, 0, 0, 1, 7, 1, 5, 3, 6
random_values13 = [2, 1, 3, 0, 2, 3, 1, 0, 0, 1, 3, 0, 0, 3, 2, 6, 4, 5, 1
random_values14 = [1, 2, 0, 3, 1, 0, 2, 3, 1, 0, 0, 3, 1, 0, 4, 1, 6, 3, 5
random_values15 = [3, 0, 2, 1, 3, 2, 0, 1, 3, 0, 0, 1, 3, 0, 0, 3, 5, 2, 7
random_values16 = [1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 2, 1, 2, 7, 1, 5, 3
random_values17 = [2, 1, 3, 0, 2, 2, 3, 1, 0, 2, 1, 3, 0, 2, 1, 3, 2, 1, 4
random_values18 = [1, 2, 0, 3, 1, 0, 2, 3, 1, 2, 0, 3, 0, 2, 6, 4, 1, 3, 5
random_values19 = [0, 0, 2, 1, 3, 0, 0, 1, 0, 0, 0, 0, 0, 2, 3, 5, 2, 7, 4
random_values20 = [0, 3, 1, 2, 0, 3, 1, 2, 0, 1, 0, 2, 0, 1, 7, 1, 5, 3, 6
random_values21 = [0, 0, 0, 0, 0, 0, 3, 0, 0, 1, 0, 1, 2, 1, 2, 3, 3, 4, 7
random_values22 = [1, 2, 0, 3, 1, 2, 0, 3, 0, 0, 2, 3, 1, 0, 5, 3, 2, 4, 7
random_values23 = [3, 0, 2, 1, 3, 0, 2, 0, 3, 2, 0, 1, 3, 2, 3, 5, 2, 7, 4
random_values24 = [0, 3, 1, 2, 0, 3, 0, 2, 0, 1, 3, 2, 0, 1, 7, 1, 5, 3, 6
random_values25 = [3, 1, 3, 3, 2, 0, 3, 0, 2, 1, 3, 3, 2, 3, 2, 6, 4, 5, 1
random_values26 = [1, 0, 3, 0, 0, 0, 0, 0, 1, 0, 1, 0, 2, 2, 4, 1, 6, 3, 5
random_values27 = [3, 0, 2, 0, 3, 2, 0, 1, 3, 0, 2, 1, 3, 0, 6, 3, 5, 2, 7
random_values28 = [3, 1, 3, 3, 2, 0, 3, 3, 2, 1, 3, 2, 3, 1, 2, 7, 1, 5, 3
random_values29 = [2, 0, 3, 0, 2, 2, 3, 1, 0, 2, 1, 3, 0, 2, 1, 3, 2, 1, 4
random_values30 = [0, 2, 0, 3, 1, 0, 2, 3, 1, 2, 0, 3, 1, 2, 6, 4, 1, 3, 5
```

In [442]:

```
input_data_scaled = scaler.transform([random_values1])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Normal
```

In [443]:

```
input_data_scaled = scaler.transform([random_values2])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [444]:

```
input_data_scaled = scaler.transform([random_values3])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [445]:
```
input_data_scaled = scaler.transform([random_values4])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [446]:
```
input_data_scaled = scaler.transform([random_values5])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [447]:
```
input_data_scaled = scaler.transform([random_values6])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Normal
```

In [448]:
```
input_data_scaled = scaler.transform([random_values7])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [449]:
```
input_data_scaled = scaler.transform([random_values8])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [450]:
```
input_data_scaled = scaler.transform([random_values9])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [451]:
```
input_data_scaled = scaler.transform([random_values10])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [452]:
```
input_data_scaled = scaler.transform([random_values11])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [453]:
```
input_data_scaled = scaler.transform([random_values12])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [454]:
```
input_data_scaled = scaler.transform([random_values13])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [455]:
```
input_data_scaled = scaler.transform([random_values14])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [456]:
```
input_data_scaled = scaler.transform([random_values15])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [457]:
```
input_data_scaled = scaler.transform([random_values16])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [458]:
```
input_data_scaled = scaler.transform([random_values17])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [459]:
```
input_data_scaled = scaler.transform([random_values18])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [460]:
```
input_data_scaled = scaler.transform([random_values19])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Normal
```

In [461]:
```
input_data_scaled = scaler.transform([random_values20])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [462]:
```
input_data_scaled = scaler.transform([random_values21])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Normal
```

In [463]:
```
input_data_scaled = scaler.transform([random_values22])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [464]:
```
input_data_scaled = scaler.transform([random_values23])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [465]:
```
input_data_scaled = scaler.transform([random_values24])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [466]:
```
input_data_scaled = scaler.transform([random_values25])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [467]:
```
input_data_scaled = scaler.transform([random_values26])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [468]:
```
input_data_scaled = scaler.transform([random_values27])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [469]:
```
input_data_scaled = scaler.transform([random_values28])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [470]:
```
input_data_scaled = scaler.transform([random_values29])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [471]:
```
input_data_scaled = scaler.transform([random_values30])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

2.1 Model for Anxiety

In [472]:
```
Anxiety.columns
```

Out[472]:
```
Index(['Q2A', 'Q4A', 'Q7A', 'Q9A', 'Q15A', 'Q19A', 'Q20A', 'Q23A', 'Q25A',
       'Q28A', 'Q30A', 'Q36A', 'Q40A', 'Q41A', 'TIPI1', 'TIPI2', 'TIPI3',
       'TIPI4', 'TIPI5', 'TIPI6', 'TIPI7', 'TIPI8', 'TIPI9', 'TIPI10',
       'education', 'urban', 'gender', 'religion', 'orientation', 'race',
       'married', 'familysize', 'age_group', 'predict'],
      dtype='object')
```

In [473]:
```
X=Anxiety[['Q2A', 'Q4A', 'Q7A', 'Q9A', 'Q15A', 'Q19A', 'Q20A', 'Q23A', 'Q2
       'Q28A', 'Q30A', 'Q36A', 'Q40A', 'Q41A', 'TIPI1', 'TIPI2', 'TIPI3',
       'TIPI4', 'TIPI5', 'TIPI6', 'TIPI7', 'TIPI8', 'TIPI9', 'TIPI10',
       'education', 'urban', 'gender', 'religion', 'orientation', 'race',
       'married', 'familysize', 'age_group']]
```

In [474]:
```
y=Anxiety[['predict']].values
y = y.flatten()
```

In [475]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.35,random_s
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [476]:
```
print('Training Set:',X_train.shape,y_train.shape)
print('Test Set:',X_test.shape,y_test.shape)
```

```
Training Set: (18428, 33) (18428,)
Test Set: (9923, 33) (9923,)
```

In [477]:

```
clf = LazyClassifier(verbose=0,ignore_warnings=True, custom_metric=None)
models, predictions = clf.fit(X_train, X_test, y_train, y_test)
print(models)
```

```
 97%|████████████████████████████████████████████████████████████████
███████    | 28/29 [07:19<00:06,  6.73s/it]

[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of tes
ting was 0.006827 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 217
[LightGBM] [Info] Number of data points in the train set: 18428, number of us
ed features: 33
[LightGBM] [Info] Start training from score -1.119615
[LightGBM] [Info] Start training from score -2.618221
[LightGBM] [Info] Start training from score -1.696291
[LightGBM] [Info] Start training from score -1.323820
[LightGBM] [Info] Start training from score -1.889264

100%|████████████████████████████████████████████████████████████████
██████████| 29/29 [07:23<00:00, 15.28s/it]
```

Model	Accuracy	Balanced Accuracy	ROC AUC	F1 Score
LogisticRegression	1.00	1.00	None	1.00
SVC	0.98	0.96	None	0.98
QuadraticDiscriminantAnalysis	0.96	0.95	None	0.96
LGBMClassifier	0.90	0.83	None	0.90
GaussianNB	0.81	0.77	None	0.82
NearestCentroid	0.75	0.74	None	0.77
ExtraTreesClassifier	0.86	0.74	None	0.84
LinearDiscriminantAnalysis	0.84	0.73	None	0.81
RandomForestClassifier	0.84	0.71	None	0.81
AdaBoostClassifier	0.71	0.70	None	0.72
BaggingClassifier	0.79	0.69	None	0.78
LinearSVC	0.82	0.66	None	0.79
BernoulliNB	0.77	0.66	None	0.76
CalibratedClassifierCV	0.80	0.64	None	0.76
KNeighborsClassifier	0.75	0.63	None	0.73
SGDClassifier	0.77	0.62	None	0.76
DecisionTreeClassifier	0.71	0.61	None	0.71
PassiveAggressiveClassifier	0.74	0.59	None	0.73
LabelSpreading	0.70	0.59	None	0.69
LabelPropagation	0.70	0.59	None	0.69
ExtraTreeClassifier	0.68	0.58	None	0.68
Perceptron	0.73	0.57	None	0.71
RidgeClassifier	0.63	0.44	None	0.52
RidgeClassifierCV	0.63	0.44	None	0.52
DummyClassifier	0.33	0.20	None	0.16

Model	Time Taken
LogisticRegression	2.61
SVC	34.73
QuadraticDiscriminantAnalysis	0.78
LGBMClassifier	3.70
GaussianNB	0.34
NearestCentroid	0.38
ExtraTreesClassifier	5.81
LinearDiscriminantAnalysis	0.91
RandomForestClassifier	8.76
AdaBoostClassifier	6.04
BaggingClassifier	3.04
LinearSVC	21.75
BernoulliNB	0.53
CalibratedClassifierCV	84.96
KNeighborsClassifier	7.91
SGDClassifier	1.12
DecisionTreeClassifier	0.67
PassiveAggressiveClassifier	0.80
LabelSpreading	140.44
LabelPropagation	114.24
ExtraTreeClassifier	0.40
Perceptron	0.87
RidgeClassifier	0.50
RidgeClassifierCV	0.53
DummyClassifier	0.30

Algorithm (1): K Nearest Neighbors

In [478]:
```
knn_anxiety = KNeighborsClassifier(n_neighbors=15).fit(X_train_scaled, y_t
```

In [479]:
```
accuracy_knn = round(accuracy_score(y_test, knn_anxiety.predict(X_test_sca
precision_knn = round(precision_score(y_test, knn_anxiety.predict(X_test_s
recall_knn = round(recall_score(y_test, knn_anxiety.predict(X_test_scaled)
f1_score_knn = round(f1_score(y_test, knn_anxiety.predict(X_test_scaled),
cross_validation_knn = round(np.mean(cross_val_score(knn_anxiety, X_train_
```

In [480]:
```
print('Accuracy:', accuracy_knn)
print('Precision:', precision_knn)
print('Recall:', recall_knn)
print('F1_Score:', f1_score_knn)
print('Cross Validation:', cross_validation_knn)
```

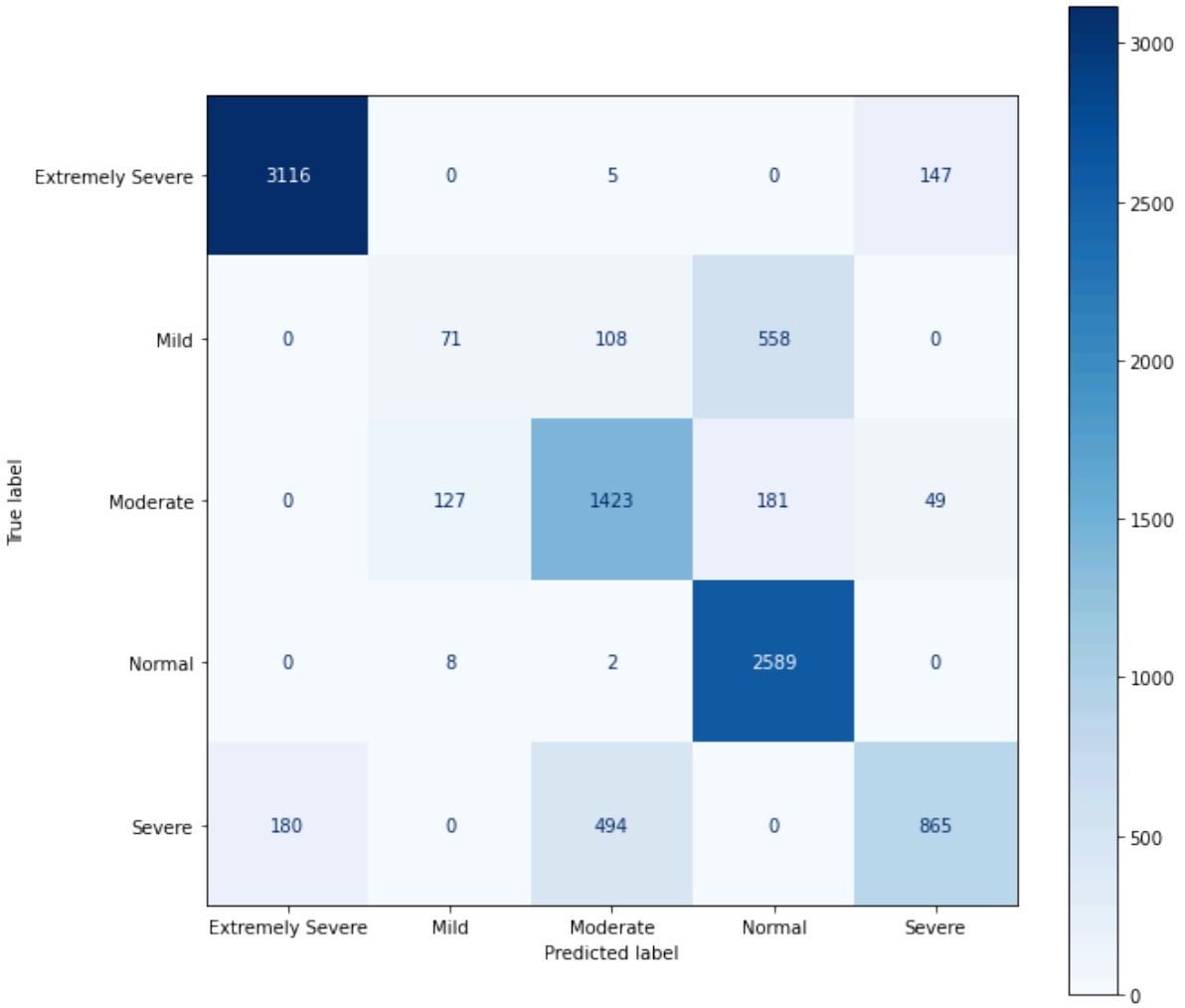
```
Accuracy: 0.813
Precision: 0.793
Recall: 0.813
F1_Score: 0.79
Cross Validation: 0.804
```

In [481]:
```
classification = classification_report(digits=4, y_true=y_test, y_pred=knn
print(classification)
```

```
                precision    recall  f1-score   support

Extremely Severe     0.9454    0.9535    0.9494      3268
            Mild     0.3447    0.0963    0.1506       737
        Moderate     0.7003    0.7994    0.7466      1780
          Normal     0.7779    0.9962    0.8736      2599
          Severe     0.8153    0.5621    0.6654      1539

        accuracy                         0.8127      9923
       macro avg     0.7167    0.6815    0.6771      9923
    weighted avg     0.7928    0.8127    0.7898      9923
```

In [482]:
```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(knn_anxiety , X_test_scaled, y_test,ax=ax, cmap='Blu
```

Out[482]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14baf28c1
30>
```



Algorithm (2): Decision Tree

In [483]:
```
decision_tree_anxity = DecisionTreeClassifier(criterion='entropy', splitte
```

In [484]:
```
accuracy_dt = round(accuracy_score(y_test, decision_tree_anxity.predict(X_
precision_dt = round(precision_score(y_test, decision_tree_anxity.predict(
recall_dt = round(recall_score(y_test, decision_tree_anxity.predict(X_test
f1_score_dt = round(f1_score(y_test, decision_tree_anxity.predict(X_test_s
cross_validation_dt = round(np.mean(cross_val_score(decision_tree_anxity,
```

In [485]:
```
print('Accuracy:', accuracy_dt)
print('Precision:', precision_dt)
print('Recall:', recall_dt)
print('F1_Score:', f1_score_dt)
print('Cross Validation:', cross_validation_dt)
```

```
Accuracy: 0.72
Precision: 0.725
Recall: 0.72
F1_Score: 0.722
Cross Validation: 0.714
```

In [486]:
```
classification = classification_report(digits=4, y_true=y_test, y_pred=dec
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     0.8803    0.8712    0.8757      3268
            Mild     0.3105    0.3446    0.3267       737
        Moderate     0.5638    0.5904    0.5768      1780
          Normal     0.8808    0.8584    0.8694      2599
          Severe     0.5163    0.4945    0.5051      1539

        accuracy                         0.7199      9923
       macro avg     0.6303    0.6318    0.6308      9923
    weighted avg     0.7249    0.7199    0.7222      9923
```

In [487]:
```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(decision_tree_anxity, X_test_scaled, y_test, ax=ax,
```

Out[487]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14bb7828a
30>
```

Algorithm (3): Random Forest

In [488]:
```
random_forest_anxity = RandomForestClassifier(n_estimators=200, min_sample
```

In [489]:
```
accuracy_rf = round(accuracy_score(y_test, random_forest_anxity.predict(X_
precision_rf = round(precision_score(y_test, random_forest_anxity.predict(
recall_rf = round(recall_score(y_test, random_forest_anxity.predict(X_test
f1_Score_rf = round(f1_score(y_test, random_forest_anxity.predict(X_test_s
cross_validation_rf = round(np.mean(cross_val_score(random_forest_anxity,
```

In [490]:

```
print('Accuracy:', accuracy_rf)
print('Precision:', precision_rf)
print('Recall:', recall_rf)
print('F1_Score:', f1_Score_rf)
print('Cross Validation:', cross_validation_rf)
```

```
Accuracy: 0.852
Precision: 0.845
Recall: 0.852
F1_Score: 0.826
Cross Validation: 0.852
```

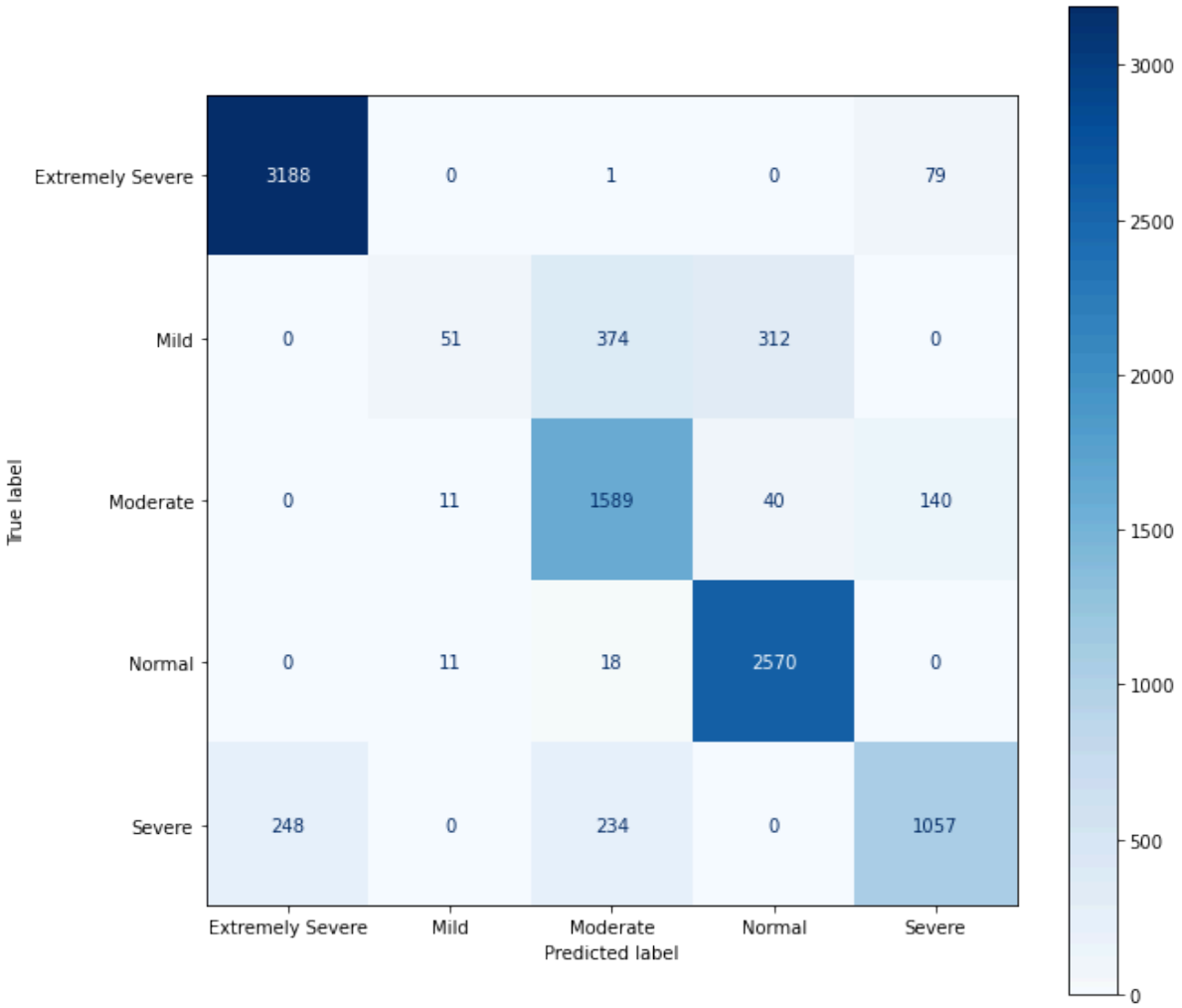
In [491]:

```
classification=classification_report(digits=4, y_true=y_test, y_pred=rando
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     0.9278    0.9755    0.9511      3268
            Mild     0.6986    0.0692    0.1259       737
        Moderate     0.7171    0.8927    0.7953      1780
          Normal     0.8795    0.9888    0.9310      2599
          Severe     0.8284    0.6868    0.7510      1539

        accuracy                         0.8521      9923
       macro avg     0.8103    0.7226    0.7109      9923
    weighted avg     0.8449    0.8521    0.8256      9923
```

In [492]:
```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(random_forest_anxity,X_test_scaled,y_test,ax=ax, cma
```

Out[492]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14bb6ed58
20>
```



Algorithm (4): Naive Bayes

In [493]:
```
naive_bayes_anxity = GaussianNB().fit(X_train_scaled,y_train)
```

In [494]:
```
accuracy_nb = round(accuracy_score(y_test, naive_bayes_anxity.predict(X_te
precision_nb = round(precision_score(y_test, naive_bayes_anxity.predict(X_
recall_nb = round(recall_score(y_test, naive_bayes_anxity.predict(X_test_s
f1_score_nb = round(f1_score(y_test, naive_bayes_anxity.predict(X_test_sca
cross_validation_nb = round(np.mean(cross_val_score(naive_bayes_anxity, X_
```

In [495]:
```
print('Accuracy:', accuracy_nb)
print('Precision:', precision_nb)
print('Recall', recall_nb)
print('F1_Score:', f1_score_nb)
print('Cross Validation:', cross_validation_nb)
```

```
Accuracy: 0.812
Precision: 0.841
Recall 0.812
F1_Score: 0.821
Cross Validation: 0.813
```

In [496]:
```
classification=classification_report(digits=4, y_true=y_test, y_pred=naive_
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     0.9907    0.8479    0.9138      3268
            Mild     0.4495    0.5319    0.4873       737
        Moderate     0.7071    0.8000    0.7507      1780
          Normal     0.9704    0.8449    0.9033      2599
          Severe     0.6439    0.8272    0.7241      1539

        accuracy                         0.8119      9923
       macro avg     0.7523    0.7704    0.7558      9923
    weighted avg     0.8405    0.8119    0.8207      9923
```

In [497]:
```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(naive_bayes_anxity, X_test_scaled,y_test,ax=ax, cmap
```

Out[497]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14bb85666
a0>
```

Algorithm (5):Logistic Regression

In [498]:
```
logistic_regression_anxity = LogisticRegression().fit(X_train_scaled, y_tr
```

In [499]:
```
accuracy_lr = round(accuracy_score(y_test, logistic_regression_anxity.pred
precision_lr = round(precision_score(y_test, logistic_regression_anxity.pr
recall_lr = round(recall_score(y_test, logistic_regression_anxity.predict(
f1_score_lr = round(f1_score(y_test, logistic_regression_anxity.predict(X_
cross_validation_lr = round(np.mean(cross_val_score(logistic_regression_an
```

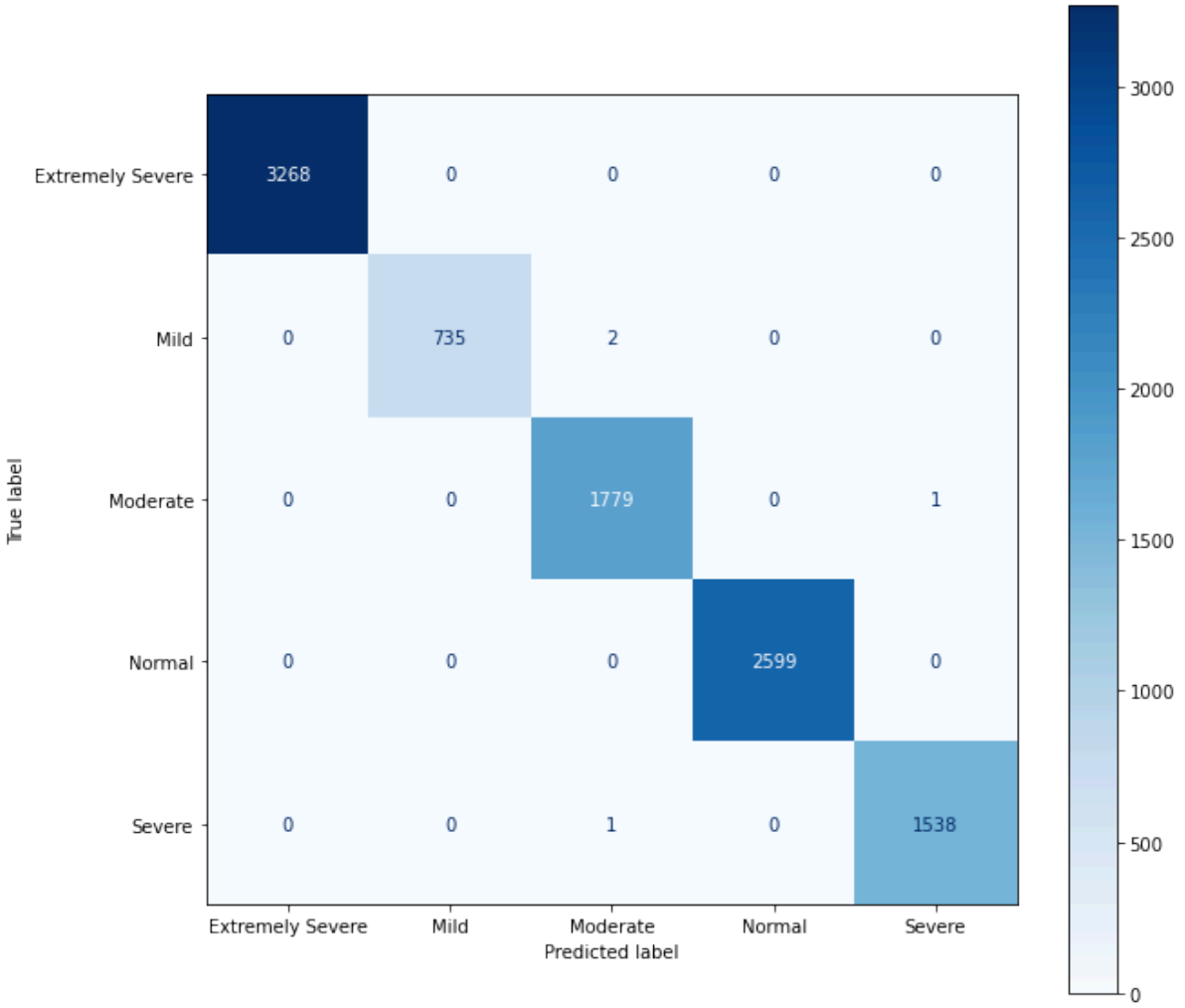
In [500]:
```
print('Accuracy:', accuracy_lr)
print('F1_Score:', f1_score_lr)
print('Recall:', recall_lr)
print('Precision:', precision_lr)
print('Cross Validation:', cross_validation_lr)
```

```
Accuracy: 1.0
F1_Score: 1.0
Recall: 1.0
Precision: 1.0
Cross Validation: 0.997
```

In [501]:
```
classification = classification_report(digits=4, y_true=y_test, y_pred=log
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     1.0000    1.0000    1.0000      3268
            Mild     1.0000    0.9973    0.9986       737
        Moderate     0.9983    0.9994    0.9989      1780
          Normal     1.0000    1.0000    1.0000      2599
          Severe     0.9994    0.9994    0.9994      1539

        accuracy                         0.9996      9923
       macro avg     0.9995    0.9992    0.9994      9923
    weighted avg     0.9996    0.9996    0.9996      9923
```

In [502]:
```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(logistic_regression_anxity, X_test_scaled, y_test, a
plt.show()
```



Algorithm (5):Support Vector Classifier

In [503]:
```
svm_anxity = SVC(C=100, gamma=0.1, kernel='rbf').fit(X_train_scaled,y_trai
```

In [504]:
```
accuracy_svm = round(accuracy_score(y_test, svm_anxity.predict(X_test_scal
precision_svm = round(precision_score(y_test, svm_anxity.predict(X_test_sc
recall_svm = round(recall_score(y_test, svm_anxity.predict(X_test_scaled),
f1_score_svm = round(f1_score(y_test, svm_anxity.predict(X_test_scaled), a
cross_validation_svm = round(np.mean(cross_val_score(svm_anxity, X_train_s
```

In [505]:
```
print('Accuracy:', accuracy_svm)
print('Precision:', precision_svm)
print('Recall:', recall_svm)
print('F1_Score:', f1_score_svm)
print('Cross Validation:', cross_validation_svm)
```

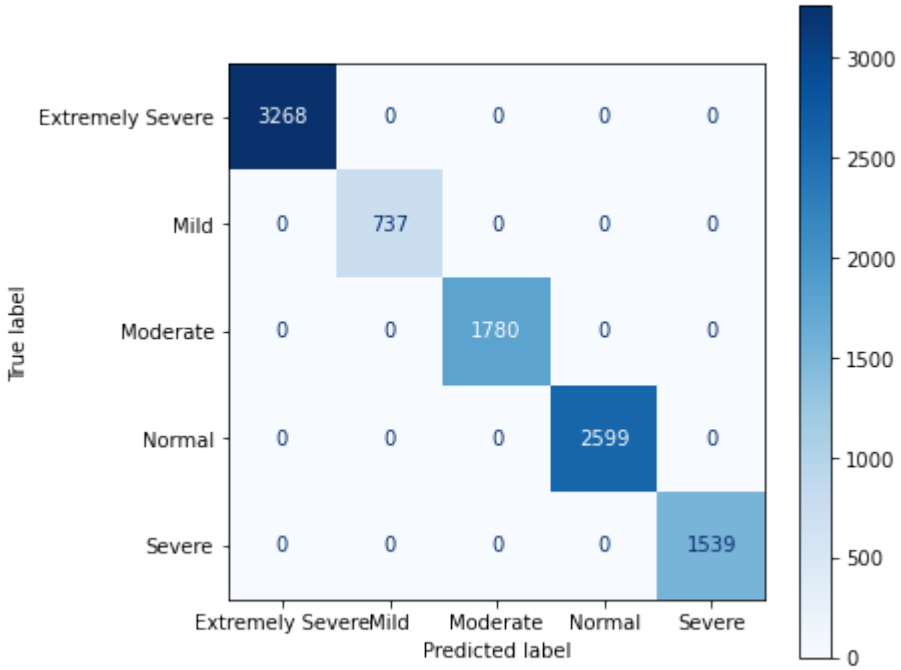
```
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1_Score: 1.0
Cross Validation: 1.0
```

In [506]:
```
classification=classification_report(digits=4, y_true=y_test, y_pred = svm
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     1.0000    1.0000    1.0000      3268
            Mild     1.0000    1.0000    1.0000       737
        Moderate     1.0000    1.0000    1.0000      1780
          Normal     1.0000    1.0000    1.0000      2599
          Severe     1.0000    1.0000    1.0000      1539

        accuracy                         1.0000      9923
       macro avg     1.0000    1.0000    1.0000      9923
    weighted avg     1.0000    1.0000    1.0000      9923
```

In [507]:
```
fig, ax = plt.subplots(figsize=(6, 6))
plot_confusion_matrix(svm_anxity, X_test_scaled, y_test,ax=ax, cmap='Blues
```

Out[507]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14bc063c5
50>
```



In [508]:
```
Result={'Model':['Random_Forest','Decision_Tree','Naive_Baise','K_Nearest_
        'Accuracy(%)':[accuracy_rf*100,accuracy_dt*100,accuracy_nb*100,acc
        'Precision(%)':[precision_rf*100,precision_dt*100,precision_nb*100
        'Recall(%)':[recall_rf*100,recall_dt*100,recall_nb*100,recall_knn*
        'F1_Score(%)':[f1_Score_rf*100,f1_score_dt*100,f1_score_nb*100,f1_
```

In [509]:
```
Result_Depression=pd.DataFrame(Result)
Result_Depression.to_csv('/Result_Anxiety.csv', index=False)
```

In [510]:
```
Result_Depression
```

Out[510]:

	Model	Accuracy(%)	Precision(%)	Recall(%)	F1_Score(%)
0	Random_Forest	85.20	84.50	85.20	82.60
1	Decision_Tree	72.00	72.50	72.00	72.20
2	Naive_Baise	81.20	84.10	81.20	82.10
3	K_Nearest_Neighbors	81.30	79.30	81.30	79.00
4	Logistic_Regression	100.00	100.00	100.00	100.00
5	SVM	100.00	100.00	100.00	100.00

Test by My Self

In [511]:
```
Anxiety
```

Out[511]:

	Q2A	Q4A	Q7A	Q9A	Q15A	Q19A	Q20A	Q23A	Q25A	Q28A	Q30A	Q36A	Q40A
0	2	0	3	2	1	0	1	0	0	0	2	0	3
1	1	3	3	3	3	3	3	3	3	3	3	3	3
2	0	2	2	2	2	0	2	2	1	1	2	1	1
3	0	0	1	0	1	0	1	0	1	0	0	0	0
4	3	3	3	3	3	3	3	3	1	3	2	3	3
...	...	...	...	...	...	...	...	...	...	...	...	...	...
28346	0	0	0	0	0	1	0	0	0	0	1	0	0
28347	3	3	3	2	3	3	3	2	2	2	2	2	2
28348	0	0	0	1	0	0	0	0	0	0	0	0	0
28349	0	1	2	2	0	0	1	0	0	2	0	1	1

In [512]:
```
1 Anxiety[Anxiety['predict'] == 'Mild']
```

Out[512]:

	Q2A	Q4A	Q7A	Q9A	Q15A	Q19A	Q20A	Q23A	Q25A	Q28A	Q30A	Q36A	Q40A	Q4
12	1	0	0	2	0	1	3	0	0	0	1	0	0	
18	2	0	1	2	0	0	1	1	0	0	0	1	1	
28	0	2	0	0	0	0	1	1	1	0	2	1	1	
33	0	0	1	1	1	0	1	0	1	0	1	1	0	
35	0	0	0	2	0	0	0	0	3	0	3	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
28265	1	0	0	2	1	0	1	0	0	1	0	1	1	
28277	1	0	0	1	1	0	1	0	0	1	1	1	2	
28295	0	2	1	1	0	0	0	0	2	0	1	1	1	
28308	0	2	0	2	0	0	0	0	2	1	0	0	2	
28316	2	0	0	1	0	0	1	0	0	0	2	0	3	

2081 rows × 34 columns

In [513]:
```
1 Anxiety.columns
```

Out[513]:
```
Index(['Q2A', 'Q4A', 'Q7A', 'Q9A', 'Q15A', 'Q19A', 'Q20A', 'Q23A', 'Q25A',
       'Q28A', 'Q30A', 'Q36A', 'Q40A', 'Q41A', 'TIPI1', 'TIPI2', 'TIPI3',
       'TIPI4', 'TIPI5', 'TIPI6', 'TIPI7', 'TIPI8', 'TIPI9', 'TIPI10',
       'education', 'urban', 'gender', 'religion', 'orientation', 'race',
       'married', 'familysize', 'age_group', 'predict'],
      dtype='object')
```

In [514]:
```
1 input_data_Severe = [2, 0, 3, 2, 1, 0, 1, 0, 0, 0, 2, 0, 3, 3, 1, 1, 7, 4,
2 input_data_scaled = scaler.transform([input_data_Severe])
```

In [515]:
```
1 prediction = svm_anxity.predict(input_data_scaled)
2 print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [516]:
```
1 input_data_Extremely_Severe = [1, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 2
2 input_data_scaled = scaler.transform([input_data_Extremely_Severe])
```

In [517]:
```
1 prediction = svm_anxity.predict(input_data_scaled)
2 print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [518]:
```
input_data_Normal = [0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 7, 6, 4, 5,
input_data_scaled = scaler.transform([input_data_Normal])
```

In [519]:
```
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Normal
```

In [520]:
```
input_data_Moderate = [0, 1, 2, 2, 0, 0, 1, 0, 0, 2, 0, 1, 1, 3, 1, 6, 5,
input_data_scaled = scaler.transform([input_data_Moderate])
```

In [521]:
```
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [522]:
```
input_data_Mild = [1, 0, 0, 2, 0, 1, 3, 0, 0, 0, 1, 0, 0, 0, 2, 2, 5, 4, 6
input_data_scaled = scaler.transform([input_data_Mild])
```

In [523]:
```
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [524]:

```
column_scales = {
    'Q2A': list(range(4)),
    'Q4A': list(range(4)),
    'Q7A': list(range(4)),
    'Q9A': list(range(4)),
    'Q15A': list(range(4)),
    'Q19A': list(range(4)),
    'Q20A': list(range(4)),
    'Q23A': list(range(4)),
    'Q25A': list(range(4)),
    'Q28A': list(range(4)),
    'Q30A': list(range(4)),
    'Q36A': list(range(4)),
    'Q40A': list(range(4)),
    'Q41A': list(range(4)),
    'TIPI1': list(range(1, 8)),
    'TIPI2': list(range(1, 8)),
    'TIPI3': list(range(1, 8)),
    'TIPI4': list(range(1, 8)),
    'TIPI5': list(range(1, 8)),
    'TIPI6': list(range(1, 8)),
    'TIPI7': list(range(1, 8)),
    'TIPI8': list(range(1, 8)),
    'TIPI9': list(range(1, 8)),
    'TIPI10': list(range(1, 8)),
    'education': list(range(1, 5)),
    'urban': list(range(1, 4)),
    'gender': list(range(1, 4)),
    'religion': list(range(1, 13)),
    'orientation': list(range(1, 6)),
    'race': [10, 20, 30, 40, 50, 60, 70],
    'married': list(range(1, 4)),
    'familysize': list(range(1, 101)),
    'age_group': list(range(1, 7))
}
```

In [525]:

```
random_lists = []
for i in range(30):
    random_list = [
        random.choice(column_scales[column]) for column in [
            'Q2A', 'Q4A', 'Q7A', 'Q9A', 'Q15A', 'Q19A', 'Q20A', 'Q23A', 'Q
            'Q28A', 'Q30A', 'Q36A', 'Q40A', 'Q41A', 'TIPI1', 'TIPI2', 'TIP
            'TIPI4', 'TIPI5', 'TIPI6', 'TIPI7', 'TIPI8', 'TIPI9', 'TIPI10'
            'education', 'urban', 'gender', 'religion', 'orientation', 'ra
            'married', 'familysize', 'age_group'
        ]
    ]
    random_lists.append(random_list)
```

In [526]:

```
for i, random_list in enumerate(random_lists, start=1):
    print(f"random_values{i} = {random_list}")
```

```
random_values1 = [0, 2, 0, 2, 1, 2, 1, 0, 3, 2, 2, 2, 3, 0, 1, 6, 2, 6, 3, 1,
5, 2, 5, 6, 4, 3, 1, 2, 5, 10, 3, 4, 6]
random_values2 = [2, 1, 2, 2, 1, 1, 3, 3, 2, 2, 2, 1, 1, 1, 3, 5, 3, 4, 4, 3,
2, 1, 2, 6, 3, 2, 2, 10, 1, 50, 3, 29, 4]
random_values3 = [3, 2, 0, 2, 0, 2, 3, 0, 1, 2, 3, 0, 1, 2, 7, 1, 5, 5, 5, 4,
1, 7, 2, 2, 1, 3, 2, 7, 2, 50, 2, 30, 5]
random_values4 = [1, 0, 1, 0, 1, 3, 2, 2, 3, 3, 1, 1, 3, 2, 5, 4, 1, 3, 5, 1,
7, 1, 3, 1, 4, 2, 2, 12, 3, 30, 1, 66, 1]
random_values5 = [3, 3, 2, 1, 2, 2, 1, 1, 1, 0, 2, 2, 0, 0, 2, 4, 5, 3, 6, 6,
7, 5, 5, 3, 3, 2, 2, 11, 3, 30, 1, 38, 3]
random_values6 = [2, 1, 3, 3, 0, 1, 0, 1, 2, 2, 0, 3, 1, 1, 7, 5, 1, 4, 2, 3,
6, 4, 4, 7, 1, 3, 3, 6, 3, 20, 1, 10, 5]
random_values7 = [0, 2, 0, 2, 1, 3, 3, 0, 1, 2, 0, 0, 2, 2, 2, 4, 3, 4, 6, 3,
1, 7, 4, 7, 2, 3, 3, 4, 2, 40, 1, 73, 6]
random_values8 = [2, 0, 2, 0, 1, 0, 2, 2, 2, 1, 0, 3, 1, 3, 6, 2, 2, 6, 4, 1,
7, 7, 2, 4, 3, 2, 2, 6, 4, 50, 3, 34, 6]
random_values9 = [3, 0, 3, 1, 3, 3, 0, 0, 0, 0, 2, 1, 1, 2, 5, 2, 4, 3, 4, 7,
7, 5, 1, 3, 1, 1, 2, 8, 5, 70, 1, 73, 2]
random_values10 = [3, 1, 1, 1, 3, 0, 1, 0, 3, 0, 2, 2, 3, 2, 7, 1, 4, 7, 5,
1, 1, 1, 1, 3, 2, 3, 1, 5, 2, 30, 2, 81, 3]
random_values11 = [1, 2, 2, 1, 0, 0, 3, 2, 1, 3, 3, 2, 0, 3, 5, 2, 1, 6, 4,
6, 3, 2, 4, 3, 2, 2, 3, 2, 4, 60, 2, 10, 3]
random_values12 = [2, 2, 0, 0, 0, 0, 3, 2, 2, 3, 2, 3, 0, 2, 4, 1, 3, 3, 2,
3, 3, 4, 1, 1, 4, 3, 3, 1, 5, 70, 1, 20, 3]
random_values13 = [3, 2, 0, 0, 3, 2, 0, 1, 3, 3, 1, 2, 0, 1, 3, 7, 4, 6, 7,
7, 6, 3, 7, 4, 1, 2, 3, 10, 1, 70, 2, 73, 5]
random_values14 = [2, 3, 0, 2, 0, 0, 3, 3, 3, 1, 0, 2, 3, 3, 6, 7, 7, 5, 5,
6, 3, 6, 4, 2, 3, 2, 2, 9, 5, 30, 1, 25, 2]
random_values15 = [3, 2, 3, 3, 2, 2, 3, 0, 2, 0, 0, 2, 3, 2, 2, 7, 6, 1, 1,
1, 7, 5, 6, 2, 2, 2, 3, 4, 2, 60, 3, 86, 6]
random_values16 = [0, 0, 3, 2, 1, 0, 3, 3, 0, 1, 1, 1, 1, 2, 3, 4, 5, 6, 7,
2, 3, 3, 7, 2, 2, 2, 3, 10, 1, 50, 1, 43, 3]
random_values17 = [3, 1, 3, 1, 0, 3, 2, 0, 0, 0, 0, 1, 3, 3, 4, 7, 2, 4, 2,
7, 3, 5, 7, 7, 2, 1, 2, 3, 3, 40, 3, 3, 2]
random_values18 = [2, 2, 2, 1, 2, 1, 0, 0, 3, 2, 0, 0, 2, 2, 2, 6, 7, 2, 4,
3, 2, 4, 7, 5, 1, 1, 2, 5, 4, 20, 3, 67, 1]
random_values19 = [2, 0, 1, 1, 3, 2, 1, 0, 1, 0, 0, 3, 2, 1, 1, 3, 7, 3, 5,
1, 4, 1, 1, 6, 1, 2, 3, 6, 1, 70, 2, 36, 1]
random_values20 = [1, 3, 0, 1, 3, 2, 1, 3, 3, 0, 2, 3, 1, 2, 1, 1, 5, 1, 4,
6, 3, 3, 2, 2, 3, 3, 2, 4, 4, 50, 1, 88, 4]
random_values21 = [2, 2, 0, 2, 0, 2, 0, 3, 3, 2, 3, 0, 0, 1, 3, 6, 7, 2, 1,
4, 1, 3, 6, 7, 1, 1, 1, 12, 5, 50, 3, 47, 5]
random_values22 = [0, 0, 3, 0, 0, 3, 2, 3, 2, 0, 2, 2, 3, 3, 2, 3, 1, 3, 3,
1, 4, 2, 4, 5, 1, 2, 2, 12, 1, 70, 2, 3, 2]
random_values23 = [1, 3, 3, 3, 0, 0, 1, 0, 0, 2, 0, 1, 2, 2, 4, 1, 1, 2, 6,
2, 4, 5, 4, 5, 1, 2, 3, 10, 1, 20, 2, 82, 2]
random_values24 = [0, 1, 3, 3, 1, 0, 2, 0, 0, 1, 1, 2, 3, 2, 1, 4, 6, 4, 5,
3, 7, 7, 4, 7, 3, 2, 2, 5, 1, 50, 2, 24, 1]
random_values25 = [2, 1, 0, 2, 0, 3, 2, 2, 2, 1, 0, 1, 0, 1, 4, 4, 1, 5, 6,
3, 2, 5, 4, 7, 3, 1, 2, 6, 2, 20, 2, 4, 5]
random_values26 = [2, 2, 1, 3, 2, 1, 0, 2, 3, 0, 2, 1, 3, 2, 1, 6, 5, 6, 4,
6, 5, 7, 1, 6, 3, 3, 1, 9, 1, 20, 1, 63, 6]
random_values27 = [1, 2, 2, 3, 3, 3, 2, 3, 1, 2, 0, 1, 0, 2, 5, 2, 6, 3, 5,
4, 4, 3, 2, 5, 1, 3, 1, 2, 4, 50, 3, 67, 5]
random_values28 = [3, 3, 2, 0, 3, 3, 2, 3, 0, 3, 2, 2, 1, 2, 4, 6, 6, 5, 2,
1, 4, 5, 7, 6, 3, 1, 1, 4, 1, 40, 1, 54, 1]
random_values29 = [1, 0, 2, 0, 1, 3, 3, 0, 1, 2, 0, 0, 2, 1, 7, 6, 2, 4, 1,
```

```
2, 1, 5, 5, 6, 4, 2, 1, 2, 4, 20, 2, 53, 3]
random_values30 = [1, 2, 2, 0, 3, 2, 0, 3, 1, 0, 3, 0, 3, 0, 7, 4, 6, 3, 5,
7, 6, 6, 7, 7, 2, 2, 2, 4, 4, 60, 2, 69, 5]
```

In [527]:

```
random_values1 = [0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 7, 6, 4, 5, 3,
random_values2 = [3, 1, 3, 0, 3, 2, 2, 2, 2, 2, 2, 3, 2, 0, 4, 1, 3, 5, 5,
random_values3 = [1, 0, 2, 2, 0, 2, 3, 2, 2, 0, 1, 3, 2, 1, 2, 2, 1, 3, 5,
random_values4 = [1, 1, 2, 0, 1, 3, 2, 1, 0, 3, 3, 1, 1, 3, 4, 5, 1, 6, 6,
random_values5 = [2, 0, 3, 1, 0, 0, 3, 3, 2, 2, 2, 1, 0, 1, 3, 4, 3, 6, 1,
random_values6 = [0, 3, 0, 3, 3, 1, 1, 3, 0, 1, 0, 1, 1, 0, 2, 6, 2, 2, 4,
random_values7 = [1, 2, 1, 0, 0, 1, 1, 2, 2, 1, 2, 2, 3, 3, 2, 6, 2, 1, 6,
random_values8 = [1, 0, 2, 2, 3, 3, 0, 1, 3, 0, 2, 1, 1, 1, 7, 7, 3, 4, 7,
random_values9 = [2, 1, 2, 1, 1, 0, 1, 2, 2, 1, 0, 2, 0, 1, 3, 2, 4, 6, 5,
random_values10 = [1, 0, 0, 0, 2, 2, 1, 0, 2, 2, 0, 3, 3, 2, 6, 5, 5, 4, 3
random_values11 = [1, 0, 0, 0, 0, 1, 0, 2, 0, 1, 0, 1, 1, 0, 6, 2, 7, 6, 1
random_values12 = [1, 2, 0, 2, 0, 0, 0, 1, 3, 2, 2, 0, 0, 2, 5, 4, 3, 4, 7
random_values13 = [2, 0, 3, 1, 0, 2, 1, 0, 3, 1, 0, 3, 3, 1, 1, 2, 7, 5, 6
random_values14 = [1, 1, 2, 1, 3, 2, 3, 1, 2, 1, 0, 3, 2, 1, 5, 3, 4, 7, 1
random_values15 = [2, 1, 0, 2, 3, 2, 0, 2, 3, 1, 0, 2, 3, 2, 3, 3, 2, 3, 1
random_values16 = [2, 0, 3, 2, 2, 0, 0, 3, 0, 3, 2, 3, 0, 2, 3, 7, 1, 6, 2
random_values17 = [2, 0, 2, 3, 3, 3, 2, 2, 2, 2, 1, 2, 0, 2, 6, 6, 7, 2, 1
random_values18 = [1, 2, 2, 2, 1, 3, 2, 2, 0, 1, 0, 2, 1, 0, 1, 1, 3, 3, 1
random_values19 = [3, 1, 1, 3, 3, 2, 3, 1, 1, 1, 0, 3, 1, 0, 1, 5, 1, 3, 3
random_values20 = [2, 1, 1, 0, 0, 3, 1, 1, 0, 2, 0, 3, 1, 0, 3, 6, 3, 3, 3
random_values21 = [3, 1, 0, 0, 2, 2, 0, 2, 0, 2, 0, 2, 3, 3, 6, 6, 7, 7, 4
random_values22 = [2, 1, 0, 0, 3, 1, 3, 3, 0, 3, 1, 0, 2, 0, 2, 4, 4, 4, 4
random_values23 = [1, 3, 1, 1, 0, 1, 3, 0, 3, 0, 0, 0, 2, 2, 4, 6, 2, 5, 2
random_values24 = [0, 1, 1, 2, 3, 2, 2, 2, 0, 2, 1, 0, 0, 2, 3, 4, 5, 6, 4
random_values25 = [2, 0, 0, 2, 3, 2, 0, 0, 2, 3, 3, 0, 2, 3, 4, 2, 2, 6, 6
random_values26 = [0, 1, 0, 3, 3, 0, 1, 1, 2, 0, 2, 3, 1, 0, 6, 5, 3, 3, 6
random_values27 = [0, 3, 2, 3, 2, 3, 1, 3, 2, 3, 0, 2, 3, 1, 4, 4, 4, 7, 4
random_values28 = [2, 2, 3, 3, 1, 0, 2, 2, 0, 3, 0, 1, 1, 0, 7, 1, 6, 5, 2
random_values29 = [0, 1, 0, 1, 3, 0, 2, 3, 0, 2, 1, 0, 3, 1, 6, 7, 2, 2, 5
random_values30 = [0, 0, 0, 0, 2, 2, 1, 0, 0, 0, 0, 0, 0, 0, 5, 1, 1, 1, 7
```

In [528]:

```
input_data_scaled = scaler.transform([random_values1])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Normal
```

In [529]:

```
input_data_scaled = scaler.transform([random_values2])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [530]:

```
input_data_scaled = scaler.transform([random_values3])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [531]:
```
input_data_scaled = scaler.transform([random_values4])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [532]:
```
input_data_scaled = scaler.transform([random_values5])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [533]:
```
input_data_scaled = scaler.transform([random_values6])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [534]:
```
input_data_scaled = scaler.transform([random_values7])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [535]:
```
input_data_scaled = scaler.transform([random_values8])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [536]:
```
input_data_scaled = scaler.transform([random_values9])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [537]:
```
input_data_scaled = scaler.transform([random_values10])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [538]:
```
input_data_scaled = scaler.transform([random_values11])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Normal
```

In [539]:
```
input_data_scaled = scaler.transform([random_values12])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [540]:
```
input_data_scaled = scaler.transform([random_values13])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [541]:
```
input_data_scaled = scaler.transform([random_values14])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [542]:
```
input_data_scaled = scaler.transform([random_values15])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [543]:
```
input_data_scaled = scaler.transform([random_values15])
prediction = svm_depression.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [544]:
```
input_data_scaled = scaler.transform([random_values16])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [545]:
```
input_data_scaled = scaler.transform([random_values17])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [546]:
```
input_data_scaled = scaler.transform([random_values18])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [547]:
```
input_data_scaled = scaler.transform([random_values19])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [548]:
```
input_data_scaled = scaler.transform([random_values20])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [549]:
```
input_data_scaled = scaler.transform([random_values21])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [550]:
```
input_data_scaled = scaler.transform([random_values22])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [551]:
```
input_data_scaled = scaler.transform([random_values23])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [552]:
```
input_data_scaled = scaler.transform([random_values24])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [553]:
```
input_data_scaled = scaler.transform([random_values25])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [554]:
```
input_data_scaled = scaler.transform([random_values26])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [555]:
```
input_data_scaled = scaler.transform([random_values27])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [556]:
```
input_data_scaled = scaler.transform([random_values28])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [557]:
```
input_data_scaled = scaler.transform([random_values29])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [558]:
```
input_data_scaled = scaler.transform([random_values30])
prediction = svm_anxity.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Normal
```

3.1 Model for Stress

In [559]:
```
Stress.columns
```

Out[559]:
```
Index(['Q1A', 'Q6A', 'Q8A', 'Q11A', 'Q12A', 'Q14A', 'Q18A', 'Q22A', 'Q27A',
       'Q29A', 'Q32A', 'Q33A', 'Q35A', 'Q39A', 'TIPI1', 'TIPI2', 'TIPI3',
       'TIPI4', 'TIPI5', 'TIPI6', 'TIPI7', 'TIPI8', 'TIPI9', 'TIPI10',
       'education', 'urban', 'gender', 'religion', 'orientation', 'race',
       'married', 'familysize', 'age_group', 'predict'],
      dtype='object')
```

In [560]:
```
X = Stress[['Q1A', 'Q6A', 'Q8A', 'Q11A', 'Q12A', 'Q14A', 'Q18A', 'Q22A', '
       'Q29A', 'Q32A', 'Q33A', 'Q35A', 'Q39A', 'TIPI1', 'TIPI2', 'TIPI3',
       'TIPI4', 'TIPI5', 'TIPI6', 'TIPI7', 'TIPI8', 'TIPI9', 'TIPI10',
       'education', 'urban', 'gender', 'religion', 'orientation', 'race',
       'married', 'familysize', 'age_group']]
```

In [561]:
```
y=Stress[['predict']].values
y = y.flatten()
```

In [562]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.35,random_s
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [563]:
```
print('Training Set:',X_train.shape,y_train.shape)
print('Test Set:',X_test.shape,y_test.shape)
```

```
Training Set: (18428, 33) (18428,)
Test Set: (9923, 33) (9923,)
```

In [564]:

```
clf = LazyClassifier(verbose=0,ignore_warnings=True, custom_metric=None)
models, predictions = clf.fit(X_train, X_test, y_train, y_test)
print(models)
```

```
 97%|████████████████████████████████████████████████████████████████
███████    | 28/29 [09:53<00:07,  7.31s/it]

[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of tes
ting was 0.004405 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 217
[LightGBM] [Info] Number of data points in the train set: 18428, number of us
ed features: 33
[LightGBM] [Info] Start training from score -2.090134
[LightGBM] [Info] Start training from score -2.051826
[LightGBM] [Info] Start training from score -1.513181
[LightGBM] [Info] Start training from score -1.124281
[LightGBM] [Info] Start training from score -1.595856

100%|████████████████████████████████████████████████████████████████
██████████| 29/29 [09:56<00:00, 20.58s/it]
```

Model	Accuracy	Balanced Accuracy	ROC AUC	F1 Score
LogisticRegression	1.00	1.00	None	1.00
SVC	0.98	0.97	None	0.98
LinearDiscriminantAnalysis	0.94	0.94	None	0.94
NuSVC	0.95	0.93	None	0.95
QuadraticDiscriminantAnalysis	0.94	0.93	None	0.94
LGBMClassifier	0.93	0.92	None	0.93
ExtraTreesClassifier	0.90	0.87	None	0.90
NearestCentroid	0.84	0.86	None	0.85
RandomForestClassifier	0.89	0.85	None	0.88
GaussianNB	0.85	0.85	None	0.86
BaggingClassifier	0.82	0.79	None	0.82
KNeighborsClassifier	0.79	0.77	None	0.79
CalibratedClassifierCV	0.83	0.76	None	0.79
LinearSVC	0.80	0.74	None	0.76
BernoulliNB	0.76	0.73	None	0.76
AdaBoostClassifier	0.71	0.71	None	0.72
DecisionTreeClassifier	0.73	0.70	None	0.73
LabelSpreading	0.72	0.69	None	0.72
LabelPropagation	0.72	0.69	None	0.72
SGDClassifier	0.72	0.67	None	0.71
ExtraTreeClassifier	0.69	0.66	None	0.69
Perceptron	0.70	0.65	None	0.69
PassiveAggressiveClassifier	0.69	0.65	None	0.69
RidgeClassifier	0.61	0.51	None	0.54
RidgeClassifierCV	0.61	0.51	None	0.54
DummyClassifier	0.32	0.20	None	0.16

Model	Time Taken
LogisticRegression	2.74
SVC	31.01
LinearDiscriminantAnalysis	1.01
NuSVC	123.28
QuadraticDiscriminantAnalysis	0.85
LGBMClassifier	3.35
ExtraTreesClassifier	5.71
NearestCentroid	0.33
RandomForestClassifier	6.84
GaussianNB	0.34
BaggingClassifier	2.86
KNeighborsClassifier	7.29
CalibratedClassifierCV	82.64
LinearSVC	20.20
BernoulliNB	0.43
AdaBoostClassifier	5.06
DecisionTreeClassifier	0.64
LabelSpreading	179.45
LabelPropagation	116.20
SGDClassifier	1.38
ExtraTreeClassifier	0.41
Perceptron	0.68
PassiveAggressiveClassifier	1.13
RidgeClassifier	0.85

```
RidgeClassifierCV                   0.82
DummyClassifier                     0.25
```

Algorithm (1): K Nearest Neighbors

In [565]:
```
knn_stress = KNeighborsClassifier(n_neighbors=15).fit(X_train_scaled, y_tr
```

In [566]:
```
accuracy_knn = round(accuracy_score(y_test, knn_stress.predict(X_test_scal
precision_knn = round(precision_score(y_test, knn_stress.predict(X_test_sc
recall_knn = round(recall_score(y_test, knn_stress.predict(X_test_scaled),
f1_score_knn = round(f1_score(y_test, knn_stress.predict(X_test_scaled), a
cross_validation_knn = round(np.mean(cross_val_score(knn_stress, X_train_s
```

In [567]:
```
print('Accuracy:', accuracy_knn)
print('Precision:', precision_knn)
print('Recall:', recall_knn)
print('F1_Score:', f1_score_knn)
print('Cross Validation:', cross_validation_knn)
```

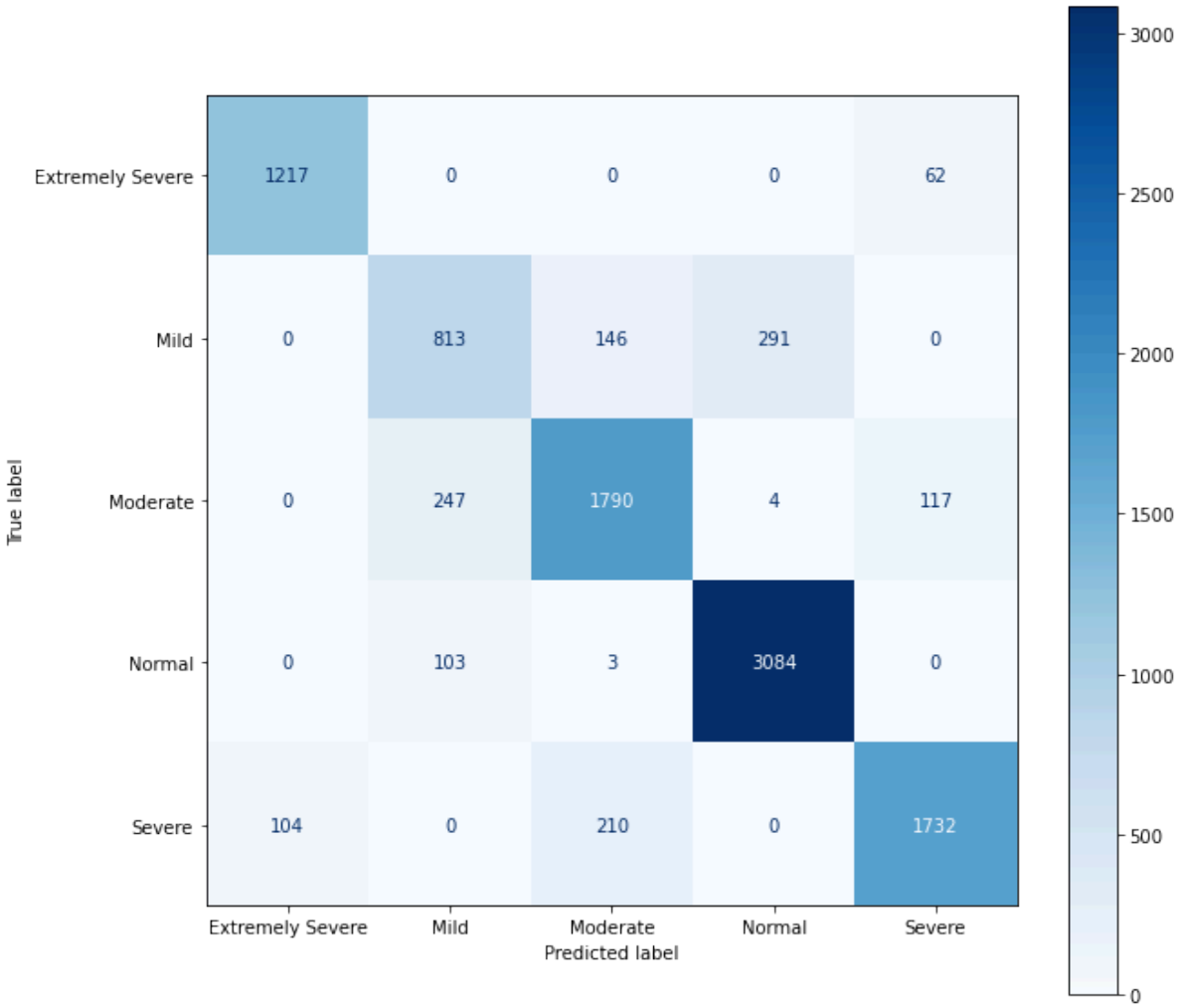
```
Accuracy: 0.87
Precision: 0.868
Recall: 0.87
F1_Score: 0.869
Cross Validation: 0.859
```

In [568]:
```
classification = classification_report(digits=4, y_true=y_test, y_pred=knn
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     0.9213    0.9515    0.9362      1279
            Mild     0.6991    0.6504    0.6738      1250
        Moderate     0.8329    0.8295    0.8312      2158
          Normal     0.9127    0.9668    0.9390      3190
          Severe     0.9063    0.8465    0.8754      2046

        accuracy                         0.8703      9923
       macro avg     0.8545    0.8489    0.8511      9923
    weighted avg     0.8682    0.8703    0.8687      9923
```

In [569]:
```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(knn_stress, X_test_scaled, y_test,ax=ax, cmap='Blues
```

Out[569]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14bc18c33
40>
```



Algorithm (2): Decision Tree

In [570]:
```
decision_tree_stress = DecisionTreeClassifier(criterion='entropy', splitte
```

In [571]:
```
accuracy_dt = round(accuracy_score(y_test, decision_tree_stress.predict(X_
precision_dt = round(precision_score(y_test, decision_tree_stress.predict(
recall_dt = round(recall_score(y_test, decision_tree_stress.predict(X_test
f1_score_dt = round(f1_score(y_test, decision_tree_stress.predict(X_test_s
cross_validation_dt = round(np.mean(cross_val_score(decision_tree_stress,
```

In [572]:
```
print('Accuracy:', accuracy_dt)
print('Precision:', precision_dt)
print('Recall:', recall_dt)
print('F1_Score:', f1_score_dt)
print('Cross Validation:', cross_validation_dt)
```

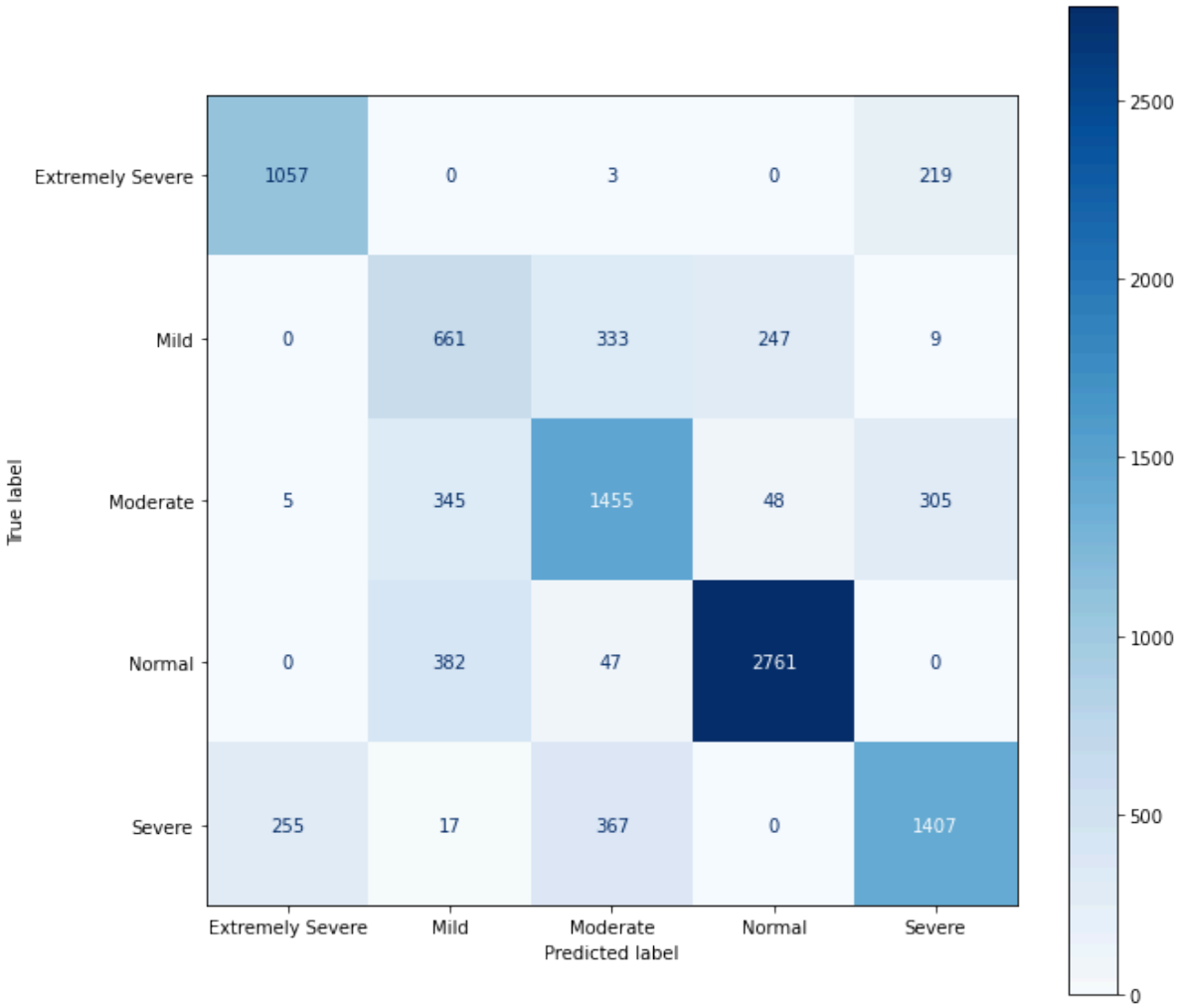
```
Accuracy: 0.74
Precision: 0.746
Recall: 0.74
F1_Score: 0.743
Cross Validation: 0.735
```

In [573]:
```
classification = classification_report(digits=4, y_true=y_test, y_pred=dec
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     0.8026    0.8264    0.8143      1279
            Mild     0.4705    0.5288    0.4979      1250
        Moderate     0.6599    0.6742    0.6670      2158
          Normal     0.9035    0.8655    0.8841      3190
          Severe     0.7253    0.6877    0.7060      2046

        accuracy                         0.7398      9923
       macro avg     0.7123    0.7165    0.7139      9923
    weighted avg     0.7462    0.7398    0.7425      9923
```

In [574]:
```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(decision_tree_stress, X_test_scaled, y_test,ax=ax, c
```

Out[574]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14baf545d
00>
```



Algorithm (3): Random Forest

In [575]:
```
random_forest_stress = RandomForestClassifier(n_estimators=200, min_sample
```

In [576]:
```
accuracy_rf = round(accuracy_score(y_test, random_forest_stress.predict(X_
precision_rf = round(precision_score(y_test, random_forest_stress.predict(
recall_rf = round(recall_score(y_test, random_forest_stress.predict(X_test
f1_Score_rf = round(f1_score(y_test, random_forest_stress.predict(X_test_s
cross_validation_rf = round(np.mean(cross_val_score(random_forest_stress,
```

In [577]:
```
print('Accuracy:', accuracy_rf)
print('Precision:', precision_rf)
print('Recall:', recall_rf)
print('F1_Score:', f1_Score_rf)
print('Cross Validation:', cross_validation_rf)
```

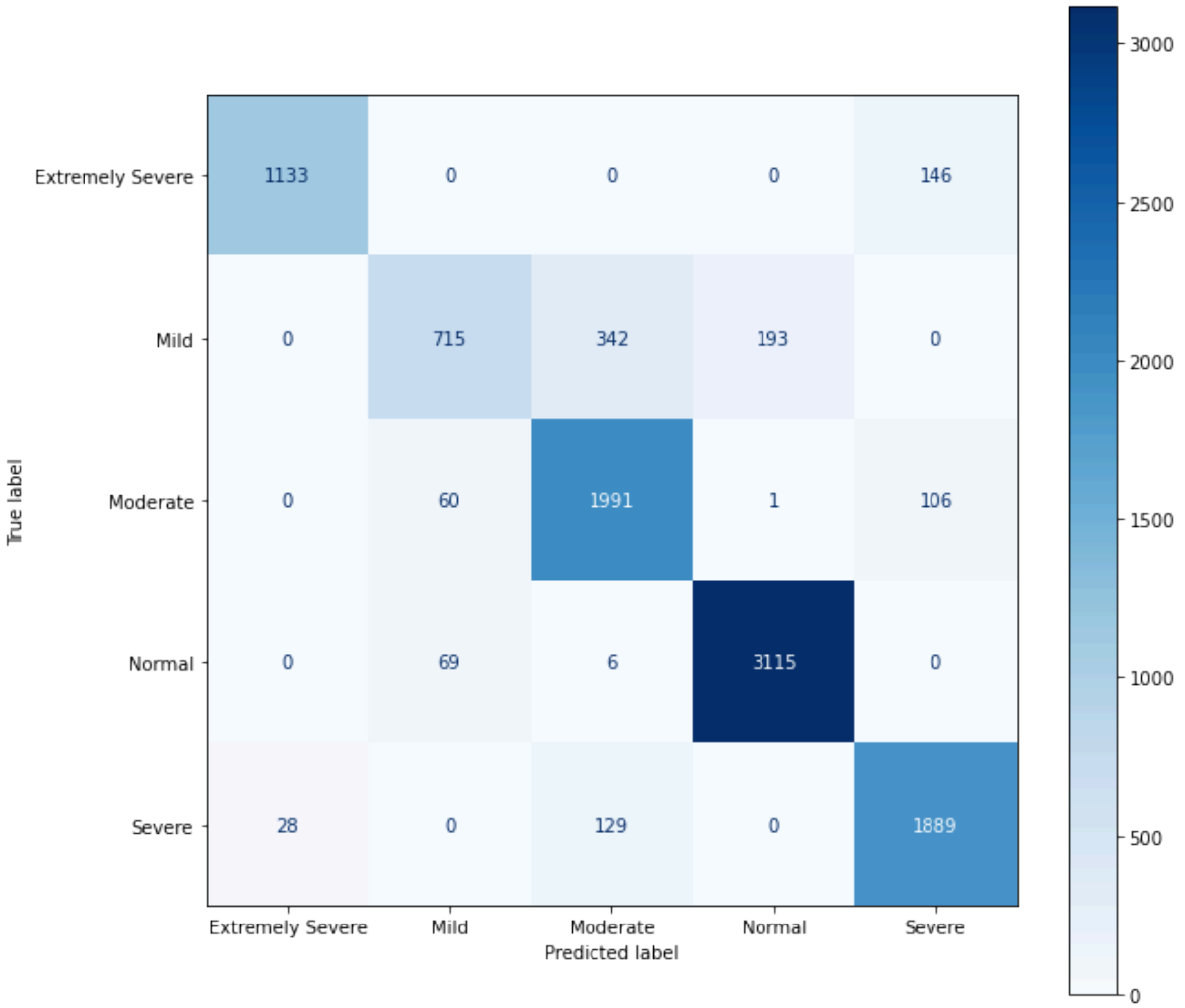
```
Accuracy: 0.891
Precision: 0.892
Recall: 0.891
F1_Score: 0.887
Cross Validation: 0.885
```

In [578]:
```
classification=classification_report(digits=4, y_true=y_test, y_pred=rando
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     0.9759    0.8858    0.9287      1279
            Mild     0.8472    0.5720    0.6829      1250
        Moderate     0.8067    0.9226    0.8608      2158
          Normal     0.9414    0.9765    0.9586      3190
          Severe     0.8823    0.9233    0.9023      2046

        accuracy                         0.8912      9923
       macro avg     0.8907    0.8560    0.8667      9923
    weighted avg     0.8925    0.8912    0.8871      9923
```

In [579]:
```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(random_forest_stress, X_test_scaled, y_test,ax=ax, c
```

Out[579]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14baf345040>
```



Algorithm (4): Naive Bayes

In [580]:
```
naive_bayse_stress = GaussianNB().fit(X_train_scaled, y_train)
```

In [581]:
```
accuracy_nb = round(accuracy_score(y_test, naive_bayse_stress.predict(X_te
precision_nb = round(precision_score(y_test, naive_bayse_stress.predict(X_
recall_nb = round(recall_score(y_test, naive_bayse_stress.predict(X_test_s
f1_score_nb = round(f1_score(y_test, naive_bayse_stress.predict(X_test_sca
cross_validation_nb = round(np.mean(cross_val_score(naive_bayse_stress, X_
```

In [582]:

```
print('Accuracy:', accuracy_nb)
print('Precision:', precision_nb)
print('Recall', recall_nb)
print('F1_Score:',f1_score_nb)
print('Cross Validation:', cross_validation_nb)
```

```
Accuracy: 0.853
Precision: 0.873
Recall 0.853
F1_Score: 0.859
Cross Validation: 0.852
```

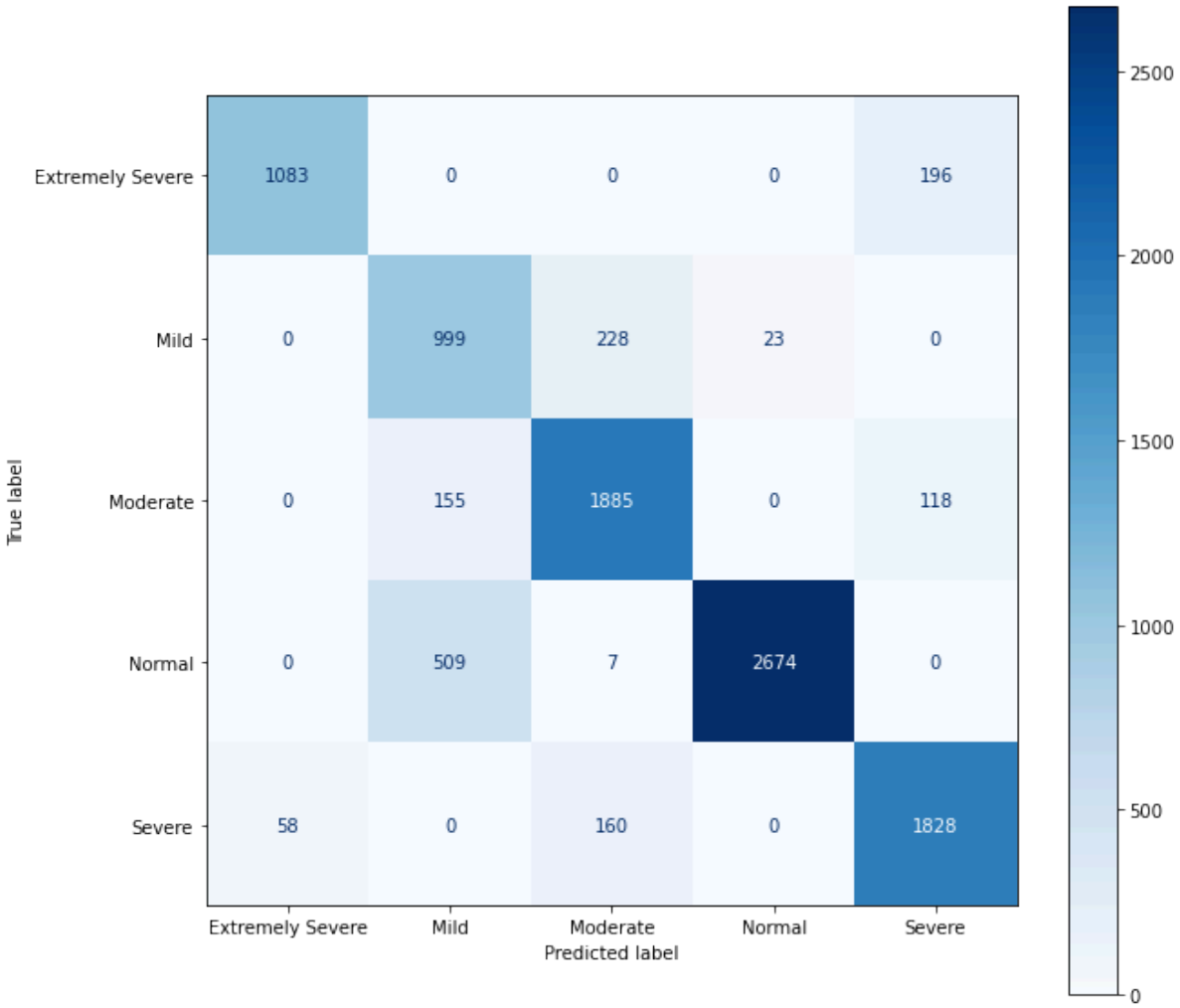
In [583]:

```
classification=classification_report(digits=4, y_true=y_test, y_pred= naiv
print(classification)
```

	precision	recall	f1-score	support
Extremely Severe	0.9492	0.8468	0.8950	1279
Mild	0.6007	0.7992	0.6859	1250
Moderate	0.8268	0.8735	0.8495	2158
Normal	0.9915	0.8382	0.9084	3190
Severe	0.8534	0.8935	0.8730	2046
accuracy			0.8535	9923
macro avg	0.8443	0.8502	0.8424	9923
weighted avg	0.8725	0.8535	0.8585	9923

In [584]:
```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(naive_bayse_stress, X_test_scaled, y_test,ax=ax, cma
```

Out[584]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14baf9f7d
f0>
```



Algorithm (5): Logistic Regression

In [585]:
```
logistic_regression_stress = LogisticRegression().fit(X_train_scaled, y_tr
```

In [586]:
```
accuracy_lr = round(accuracy_score(y_test, logistic_regression_stress.pred
precision_lr = round(precision_score(y_test, logistic_regression_stress.pr
recall_lr = round(recall_score(y_test, logistic_regression_stress.predict(
f1_score_lr = round(f1_score(y_test, logistic_regression_stress.predict(X_
cross_validation_lr = round(np.mean(cross_val_score(logistic_regression_st
```

In [587]:
```
print('Accuracy:', accuracy_lr)
print('Precision:', precision_lr)
print('Recall:', recall_lr)
print('F1_Score:', f1_score_lr)
print('Cross Validation:', cross_validation_lr)
```

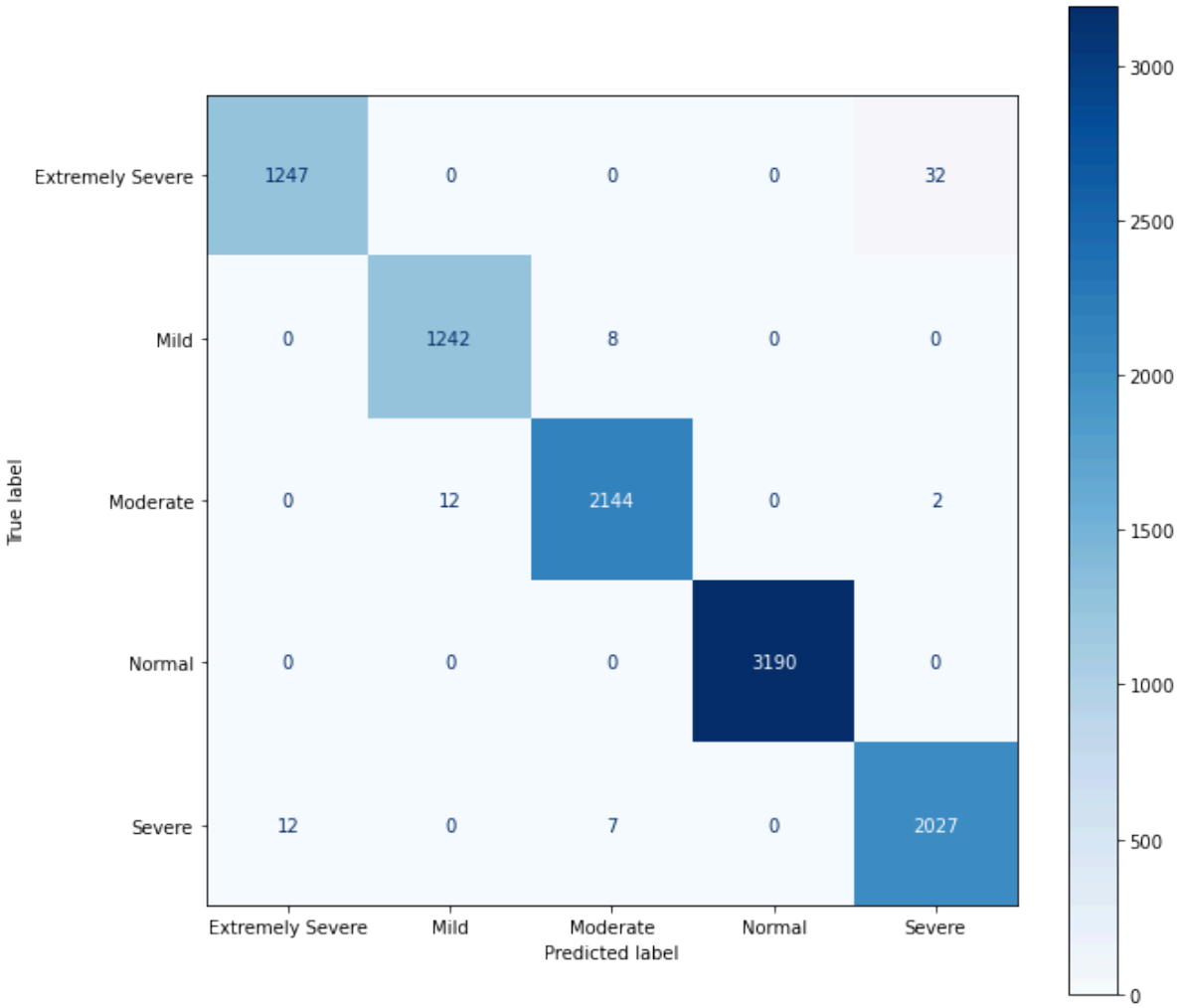
```
Accuracy: 0.993
Precision: 0.993
Recall: 0.993
F1_Score: 0.993
Cross Validation: 0.989
```

In [588]:
```
classification = classification_report(digits=4, y_true=y_test, y_pred=log
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     0.9905    0.9750    0.9827      1279
            Mild     0.9904    0.9936    0.9920      1250
        Moderate     0.9931    0.9935    0.9933      2158
          Normal     1.0000    1.0000    1.0000      3190
          Severe     0.9835    0.9907    0.9871      2046

        accuracy                         0.9926      9923
       macro avg     0.9915    0.9906    0.9910      9923
    weighted avg     0.9927    0.9926    0.9926      9923
```

In [589]:
```
1 fig, ax = plt.subplots(figsize=(10, 10))
2 plot_confusion_matrix(logistic_regression_stress, X_test_scaled, y_test, a
```

Out[589]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14baf2ff3
d0>
```



Algorithm (6): Support Vector Classifier

In [590]:
```
1 svm_stress = SVC(C=100, gamma=0.1, kernel='rbf').fit(X_train_scaled, y_tra
```

In [591]:
```
1 accuracy_svm = round(accuracy_score(y_test, svm_stress.predict(X_test_scal
2 precision_svm = round(precision_score(y_test, svm_stress.predict(X_test_sc
3 recall_svm = round(recall_score(y_test, svm_stress.predict(X_test_scaled),
4 f1_score_svm = round(f1_score(y_test,svm_stress.predict(X_test_scaled), av
5 cross_validation_svm = round(np.mean(cross_val_score(svm_stress, X_train_s
```

In [592]:
```
print('Accuracy:', accuracy_svm)
print('Recall:', recall_svm)
print('Precision:', precision_svm)
print('F1_Score:', f1_score_svm)
print('Cross Validation:', cross_validation_svm)
```

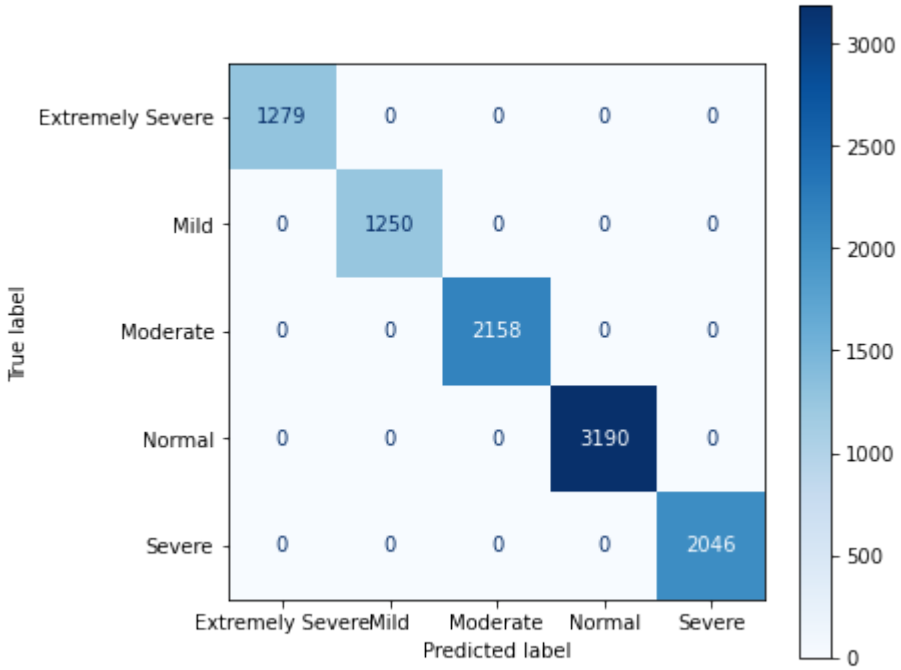
```
Accuracy: 1.0
Recall: 1.0
Precision: 1.0
F1_Score: 1.0
Cross Validation: 1.0
```

In [593]:
```
classification = classification_report(digits=4, y_true=y_test, y_pred=svm
print(classification)
```

```
                  precision    recall  f1-score   support

Extremely Severe     1.0000    1.0000    1.0000      1279
            Mild     1.0000    1.0000    1.0000      1250
        Moderate     1.0000    1.0000    1.0000      2158
          Normal     1.0000    1.0000    1.0000      3190
          Severe     1.0000    1.0000    1.0000      2046

        accuracy                         1.0000      9923
       macro avg     1.0000    1.0000    1.0000      9923
    weighted avg     1.0000    1.0000    1.0000      9923
```

In [594]:
```
fig, ax = plt.subplots(figsize=(6, 6))
plot_confusion_matrix(svm_stress, X_test_scaled, y_test, ax=ax, cmap='Blue
```

Out[594]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14bacaf1c
70>
```



In [595]:
```
Result={'Model':['Random_Forest','Decision_Tree','Naive_Baise','K_Nearest_
        'Accuracy(%)':[accuracy_rf*100,accuracy_dt*100,accuracy_nb*100,acc
        'Precision(%)':[precision_rf*100,precision_dt*100,precision_nb*100
        'Recall(%)':[recall_rf*100,recall_dt*100,recall_nb*100,recall_knn*
        'F1_Score(%)':[f1_Score_rf*100,f1_score_dt*100,f1_score_nb*100,f1_
```

In [596]:
```
Result_Stress=pd.DataFrame(Result)
Result_Stress.to_csv('/Result_Stress.csv', index=False)
```

In [597]:
```
Result_Stress
```

Out[597]:

	Model	Accuracy(%)	Precision(%)	Recall(%)	F1_Score(%)
0	Random_Forest	89.10	89.20	89.10	88.70
1	Decision_Tree	74.00	74.60	74.00	74.30
2	Naive_Baise	85.30	87.30	85.30	85.90
3	K_Nearest_Neighbors	87.00	86.80	87.00	86.90
4	Logistic_Regression	99.30	99.30	99.30	99.30
5	SVM	100.00	100.00	100.00	100.00

Test by My Self

In [598]:
```
Stress
```

Out[598]:

	Q1A	Q6A	Q8A	Q11A	Q12A	Q14A	Q18A	Q22A	Q27A	Q29A	Q32A	Q33A	Q35A	Q3
0	1	2	1	1	0	3	0	0	3	2	0	1	0	
1	1	1	3	1	3	3	3	2	1	1	3	3	2	
2	0	0	2	0	1	1	1	0	0	1	1	3	1	
3	0	1	0	1	0	1	1	0	1	0	0	0	0	
4	3	3	3	3	3	2	3	3	1	3	1	3	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
28346	1	1	1	1	1	1	1	1	1	1	1	1	1	
28347	2	3	3	3	3	3	2	3	2	2	2	2	2	
28348	1	0	0	0	0	0	0	0	1	1	0	1	0	
28349	2	2	3	2	2	3	2	3	3	2	2	3	2	
28350	1	1	0	2	0	0	2	1	2	2	1	1	1	

28351 rows × 34 columns

In [599]:
```
Stress.columns
```

Out[599]:
```
Index(['Q1A', 'Q6A', 'Q8A', 'Q11A', 'Q12A', 'Q14A', 'Q18A', 'Q22A', 'Q27A',
       'Q29A', 'Q32A', 'Q33A', 'Q35A', 'Q39A', 'TIPI1', 'TIPI2', 'TIPI3',
       'TIPI4', 'TIPI5', 'TIPI6', 'TIPI7', 'TIPI8', 'TIPI9', 'TIPI10',
       'education', 'urban', 'gender', 'religion', 'orientation', 'race',
       'married', 'familysize', 'age_group', 'predict'],
      dtype='object')
```

In [600]:
```
Depression[Depression['predict'] == 'Moderate']
```

Out[600]:

	Q3A	Q5A	Q10A	Q13A	Q16A	Q17A	Q21A	Q24A	Q26A	Q31A	Q34A	Q37A	Q38A	
0	1	2	2	0	1	2	0	0	1	2	3	1	0	
6	0	0	2	2	2	2	2	1	2	0	1	3	1	
7	0	2	0	3	2	3	0	2	0	1	0	0	0	
10	1	1	1	1	2	1	1	1	1	2	1	1	0	
11	1	2	1	0	2	0	0	2	0	2	0	0	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
28315	0	1	1	2	1	1	2	1	2	1	1	1	1	
28316	1	0	2	1	1	1	0	1	1	1	1	3	0	
28317	1	1	2	3	1	2	0	1	2	0	3	1	0	
28341	1	2	2	1	2	2	1	1	1	1	2	1	1	
28349	1	2	0	3	0	1	1	1	2	1	1	0	1	

5277 rows × 34 columns

In [601]:
```
input_data_Mild = [1, 2, 1, 1, 0, 3, 0, 0, 3, 2, 0, 1, 0, 2, 1, 1, 7, 4, 6
input_data_scaled = scaler.transform([input_data_Mild])
```

In [602]:
```
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [603]:
```
input_data_Severe = [1, 1, 3, 1, 3, 3, 3, 2, 1, 1, 3, 3, 2, 2, 2, 5, 3, 6,
input_data_scaled = scaler.transform([input_data_Severe])
```

In [604]:
```
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [605]:
```
input_data_Normal = [0, 0, 2, 0, 1, 1, 1, 0, 0, 1, 1, 3, 1, 3, 2, 5, 6, 5,
input_data_scaled = scaler.transform([input_data_Normal])
```

In [606]:
```
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Normal
```

In [607]:
```
input_data_Extremely_severe = [2, 3, 3, 3, 3, 3, 2, 3, 2, 2, 2, 2, 2, 2, 4
input_data_scaled = scaler.transform([input_data_Extremely_Severe])
```

In [608]:
```
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [609]:
```
input_data_Moderate = [1, 2, 2, 0, 1, 2, 0, 0, 1, 2, 3, 1, 0, 1, 1, 1, 7,
input_data_scaled = scaler.transform([input_data_Moderate])
```

In [610]:
```
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [611]:

```
column_scales = {
    'Q1A': list(range(4)),
    'Q6A': list(range(4)),
    'Q8A': list(range(4)),
    'Q11A': list(range(4)),
    'Q12A': list(range(4)),
    'Q14A': list(range(4)),
    'Q18A': list(range(4)),
    'Q22A': list(range(4)),
    'Q27A': list(range(4)),
    'Q29A': list(range(4)),
    'Q32A': list(range(4)),
    'Q33A': list(range(4)),
    'Q35A': list(range(4)),
    'Q39A': list(range(4)),
    'TIPI1': list(range(1, 8)),
    'TIPI2': list(range(1, 8)),
    'TIPI3': list(range(1, 8)),
    'TIPI4': list(range(1, 8)),
    'TIPI5': list(range(1, 8)),
    'TIPI6': list(range(1, 8)),
    'TIPI7': list(range(1, 8)),
    'TIPI8': list(range(1, 8)),
    'TIPI9': list(range(1, 8)),
    'TIPI10': list(range(1, 8)),
    'education': list(range(1, 5)),
    'urban': list(range(1, 4)),
    'gender': list(range(1, 4)),
    'religion': list(range(1, 13)),
    'orientation': list(range(1, 6)),
    'race': [10, 20, 30, 40, 50, 60, 70],
    'married': list(range(1, 4)),
    'familysize': list(range(1, 101)),
    'age_group': list(range(1, 7))
}
```

In [612]:

```
random_lists = []
for i in range(30):
    random_list = [
        random.choice(column_scales[column]) for column in [
            'Q1A', 'Q6A', 'Q8A', 'Q11A', 'Q12A', 'Q14A', 'Q18A', 'Q22A', '
       'Q29A', 'Q32A', 'Q33A', 'Q35A', 'Q39A', 'TIPI1', 'TIPI2', 'TIPI3',
            'TIPI4', 'TIPI5', 'TIPI6', 'TIPI7', 'TIPI8', 'TIPI9', 'TIPI10'
            'education', 'urban', 'gender', 'religion', 'orientation', 'ra
            'married', 'familysize', 'age_group'
        ]
    ]
    random_lists.append(random_list)
```

In [613]:

```
for i, random_list in enumerate(random_lists, start=1):
    print(f"random_values{i} = {random_list}")
```

```
random_values1 = [2, 2, 0, 0, 1, 3, 2, 2, 2, 3, 1, 2, 3, 0, 5, 4, 4, 1, 5, 1,
6, 6, 7, 5, 4, 1, 1, 11, 1, 70, 1, 82, 4]
random_values2 = [2, 0, 3, 2, 2, 3, 1, 3, 3, 3, 1, 2, 1, 2, 5, 3, 7, 2, 2, 5,
7, 5, 4, 1, 2, 1, 2, 4, 4, 50, 3, 17, 3]
random_values3 = [3, 0, 0, 3, 3, 2, 0, 1, 2, 2, 0, 2, 3, 0, 4, 1, 4, 5, 6, 3,
2, 1, 6, 1, 1, 2, 3, 3, 3, 10, 1, 6, 1]
random_values4 = [0, 1, 0, 2, 1, 2, 0, 2, 1, 1, 2, 2, 1, 3, 5, 1, 4, 7, 1, 6,
5, 7, 2, 7, 2, 2, 3, 12, 1, 60, 2, 55, 5]
random_values5 = [1, 1, 3, 1, 1, 3, 3, 3, 0, 2, 3, 3, 3, 2, 1, 4, 5, 2, 5, 3,
1, 1, 5, 1, 4, 2, 2, 11, 5, 20, 2, 59, 6]
random_values6 = [2, 2, 0, 2, 3, 3, 0, 2, 1, 1, 0, 0, 3, 3, 3, 7, 5, 5, 4, 1,
5, 3, 2, 7, 1, 1, 3, 10, 5, 30, 1, 62, 5]
random_values7 = [0, 1, 0, 3, 0, 1, 3, 2, 0, 3, 0, 2, 0, 2, 1, 7, 5, 1, 4, 5,
6, 4, 2, 2, 2, 3, 1, 12, 2, 40, 3, 16, 5]
random_values8 = [2, 3, 3, 2, 2, 0, 1, 3, 3, 2, 1, 0, 1, 0, 3, 2, 1, 6, 1, 5,
5, 6, 7, 5, 4, 2, 3, 10, 4, 70, 2, 72, 5]
random_values9 = [1, 0, 3, 1, 2, 1, 1, 3, 1, 1, 3, 1, 0, 0, 6, 2, 4, 1, 6, 6,
4, 1, 2, 2, 3, 3, 3, 8, 1, 20, 2, 100, 2]
random_values10 = [3, 0, 2, 1, 0, 2, 1, 3, 3, 3, 0, 0, 3, 3, 2, 6, 5, 4, 6,
5, 5, 1, 1, 3, 3, 1, 3, 6, 2, 70, 3, 58, 3]
random_values11 = [0, 2, 0, 3, 3, 2, 0, 3, 1, 3, 2, 1, 3, 2, 2, 3, 7, 4, 6,
6, 2, 3, 2, 7, 2, 3, 2, 2, 4, 20, 2, 32, 1]
random_values12 = [2, 1, 3, 0, 1, 2, 3, 0, 1, 0, 3, 2, 3, 1, 5, 3, 7, 5, 2,
7, 2, 3, 2, 6, 4, 2, 3, 8, 4, 20, 2, 7, 2]
random_values13 = [1, 0, 1, 2, 3, 2, 0, 2, 0, 1, 0, 0, 0, 1, 4, 5, 6, 5, 2,
6, 4, 7, 6, 4, 3, 3, 3, 6, 3, 40, 3, 21, 1]
random_values14 = [0, 3, 1, 2, 3, 1, 0, 2, 3, 1, 2, 3, 0, 3, 3, 2, 5, 1, 3,
3, 5, 5, 4, 2, 2, 1, 2, 5, 3, 20, 2, 29, 6]
random_values15 = [0, 3, 0, 0, 0, 1, 2, 1, 0, 1, 1, 2, 3, 2, 5, 4, 3, 5, 7,
4, 1, 1, 2, 6, 3, 3, 1, 2, 5, 60, 2, 68, 3]
random_values16 = [3, 3, 3, 0, 1, 1, 3, 2, 3, 1, 3, 0, 0, 1, 7, 7, 5, 1, 6,
6, 3, 5, 1, 3, 4, 2, 2, 10, 2, 10, 3, 19, 1]
random_values17 = [0, 2, 3, 1, 3, 0, 1, 0, 3, 1, 2, 0, 0, 1, 7, 1, 1, 4, 4,
5, 3, 5, 5, 3, 3, 1, 3, 12, 5, 30, 3, 44, 4]
random_values18 = [0, 1, 1, 1, 2, 0, 1, 1, 3, 0, 0, 0, 0, 3, 3, 1, 1, 6, 2,
4, 6, 4, 6, 3, 2, 1, 3, 5, 3, 40, 3, 36, 3]
random_values19 = [1, 0, 0, 0, 2, 2, 1, 2, 1, 2, 1, 3, 3, 2, 6, 1, 1, 4, 5,
6, 1, 5, 6, 3, 4, 2, 1, 5, 2, 30, 3, 36, 3]
random_values20 = [2, 3, 2, 2, 0, 3, 2, 3, 1, 3, 1, 2, 2, 1, 5, 1, 2, 6, 1,
4, 2, 6, 6, 4, 4, 1, 2, 2, 4, 30, 3, 1, 3]
random_values21 = [3, 0, 0, 2, 1, 2, 2, 2, 0, 2, 0, 1, 1, 1, 4, 7, 5, 3, 5,
4, 3, 6, 4, 5, 1, 2, 2, 9, 5, 70, 1, 3, 2]
random_values22 = [3, 3, 1, 2, 3, 3, 2, 0, 1, 2, 2, 0, 3, 1, 7, 2, 5, 4, 1,
2, 5, 2, 4, 5, 2, 2, 1, 5, 3, 10, 1, 85, 1]
random_values23 = [0, 0, 2, 3, 0, 2, 0, 3, 3, 0, 1, 2, 2, 0, 3, 7, 3, 4, 7,
1, 4, 7, 2, 7, 1, 2, 2, 8, 3, 20, 3, 65, 6]
random_values24 = [3, 1, 0, 3, 2, 2, 2, 1, 2, 0, 1, 2, 1, 2, 5, 3, 7, 7, 5,
5, 1, 6, 4, 7, 1, 1, 1, 10, 1, 40, 3, 51, 3]
random_values25 = [2, 3, 1, 1, 3, 3, 0, 1, 1, 3, 0, 1, 3, 0, 3, 3, 6, 4, 4,
2, 1, 2, 7, 3, 4, 1, 3, 7, 1, 10, 2, 73, 6]
random_values26 = [0, 1, 3, 3, 3, 0, 0, 2, 0, 2, 1, 2, 3, 0, 7, 1, 5, 6, 2,
1, 2, 4, 5, 7, 1, 2, 1, 3, 2, 60, 2, 90, 1]
random_values27 = [1, 1, 0, 0, 1, 0, 3, 1, 2, 1, 0, 2, 3, 3, 7, 6, 5, 7, 4,
3, 6, 4, 3, 2, 4, 1, 3, 7, 4, 40, 1, 41, 1]
random_values28 = [1, 1, 2, 1, 0, 2, 2, 3, 0, 0, 3, 2, 3, 1, 4, 3, 6, 5, 7,
2, 7, 4, 4, 1, 3, 3, 2, 5, 5, 40, 1, 79, 4]
random_values29 = [0, 3, 3, 3, 1, 3, 1, 0, 2, 2, 0, 2, 1, 0, 4, 4, 6, 2, 1,
```

```
6, 3, 6, 1, 3, 3, 3, 3, 1, 5, 20, 1, 65, 3]
random_values30 = [2, 2, 2, 2, 3, 0, 2, 3, 2, 1, 1, 1, 3, 2, 2, 2, 7, 3, 1,
3, 5, 2, 1, 2, 3, 2, 3, 9, 3, 50, 1, 94, 5]
```

In [614]:

```
random_values1 = [2, 0, 1, 2, 3, 3, 0, 0, 0, 0, 3, 0, 0, 3, 4, 2, 1, 3, 2,
random_values2 = [1, 0, 1, 3, 1, 1, 3, 2, 2, 3, 2, 1, 3, 0, 3, 5, 5, 2, 6,
random_values3 = [3, 1, 1, 1, 1, 1, 0, 3, 2, 1, 1, 3, 2, 1, 6, 5, 2, 4, 6,
random_values4 = [1, 1, 0, 3, 2, 0, 2, 1, 1, 2, 2, 2, 0, 2, 3, 6, 1, 2, 3,
random_values5 = [3, 1, 2, 0, 1, 1, 1, 3, 1, 3, 2, 2, 2, 3, 4, 5, 7, 1, 6,
random_values6 = [3, 3, 3, 2, 2, 3, 3, 3, 3, 2, 3, 2, 2, 0, 4, 6, 6, 4, 3,
random_values7 = [1, 3, 1, 1, 1, 0, 1, 3, 3, 2, 1, 0, 1, 3, 7, 1, 7, 7, 4,
random_values8 = [1, 2, 1, 0, 3, 3, 0, 0, 2, 3, 1, 0, 2, 3, 6, 6, 6, 6, 7,
random_values9 = [2, 3, 3, 2, 2, 3, 0, 2, 0, 1, 1, 0, 1, 0, 2, 2, 4, 7, 3,
random_values10 = [2, 2, 3, 0, 0, 3, 1, 3, 3, 1, 3, 3, 3, 1, 7, 7, 4, 5, 5
random_values11 = [1, 2, 2, 1, 2, 3, 0, 0, 1, 0, 1, 0, 3, 2, 1, 1, 3, 3, 7
random_values12 = [2, 2, 2, 1, 0, 3, 0, 1, 1, 1, 1, 0, 3, 0, 7, 4, 3, 5, 6
random_values13 = [1, 2, 3, 0, 0, 2, 3, 1, 3, 1, 3, 0, 0, 3, 2, 4, 4, 3, 1
random_values14 = [1, 0, 2, 1, 0, 3, 0, 1, 3, 0, 0, 0, 3, 3, 1, 1, 7, 2, 7
random_values15 = [0, 0, 3, 2, 1, 3, 2, 0, 0, 3, 2, 1, 2, 2, 6, 7, 3, 7, 3
random_values16 = [1, 2, 0, 0, 1, 0, 0, 0, 3, 2, 2, 3, 2, 1, 2, 3, 3, 6, 5
random_values17 = [2, 3, 3, 1, 2, 0, 0, 1, 2, 1, 0, 0, 2, 3, 2, 7, 3, 1, 2
random_values18 = [3, 2, 2, 3, 3, 2, 1, 2, 2, 1, 2, 2, 3, 1, 1, 7, 7, 5, 1
random_values19 = [2, 3, 0, 3, 2, 2, 1, 1, 0, 3, 2, 3, 1, 2, 3, 1, 7, 6, 4
random_values20 = [3, 1, 2, 1, 0, 0, 1, 2, 2, 3, 1, 2, 0, 1, 1, 6, 4, 7, 5
random_values21 = [3, 3, 0, 3, 1, 0, 1, 1, 2, 0, 0, 2, 3, 1, 4, 1, 4, 3, 3
random_values22 = [0, 2, 1, 0, 2, 2, 0, 2, 0, 3, 1, 1, 2, 3, 7, 4, 2, 5, 6
random_values23 = [3, 0, 1, 2, 3, 2, 3, 3, 1, 3, 1, 3, 0, 0, 5, 7, 6, 3, 7
random_values24 = [2, 3, 1, 0, 2, 3, 3, 2, 0, 3, 2, 0, 1, 3, 4, 5, 2, 1, 3
random_values25 = [0, 2, 2, 1, 0, 0, 2, 3, 2, 1, 0, 0, 3, 1, 7, 1, 2, 2, 2
random_values26 = [0, 0, 3, 0, 2, 1, 2, 1, 2, 0, 2, 1, 2, 1, 6, 4, 5, 6, 6
random_values27 = [3, 3, 1, 1, 0, 3, 1, 0, 3, 1, 2, 2, 0, 3, 1, 4, 4, 3, 4
random_values28 = [3, 0, 1, 0, 0, 2, 3, 2, 2, 1, 0, 0, 0, 0, 3, 7, 5, 1, 5
random_values29 = [2, 0, 0, 1, 0, 2, 0, 2, 2, 2, 3, 1, 2, 1, 2, 1, 6, 3, 2
random_values30 = [0, 1, 3, 2, 3, 3, 1, 2, 2, 0, 3, 2, 1, 3, 4, 6, 3, 5, 7
```

In [615]:

```
input_data_scaled = scaler.transform([random_values1])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [616]:

```
input_data_scaled = scaler.transform([random_values2])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [617]:

```
input_data_scaled = scaler.transform([random_values3])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [618]:
```
input_data_scaled = scaler.transform([random_values4])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [619]:
```
input_data_scaled = scaler.transform([random_values5])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [620]:
```
input_data_scaled = scaler.transform([random_values6])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Extremely Severe
```

In [621]:
```
input_data_scaled = scaler.transform([random_values7])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [622]:
```
input_data_scaled = scaler.transform([random_values8])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [623]:
```
input_data_scaled = scaler.transform([random_values9])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [624]:
```
input_data_scaled = scaler.transform([random_values10])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [625]:
```
input_data_scaled = scaler.transform([random_values11])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [626]:
```
input_data_scaled = scaler.transform([random_values12])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [627]:
```
input_data_scaled = scaler.transform([random_values13])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [628]:
```
input_data_scaled = scaler.transform([random_values14])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [629]:
```
input_data_scaled = scaler.transform([random_values15])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [630]:
```
input_data_scaled = scaler.transform([random_values16])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [631]:
```
input_data_scaled = scaler.transform([random_values17])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [632]:
```
input_data_scaled = scaler.transform([random_values18])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [633]:
```
input_data_scaled = scaler.transform([random_values19])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [634]:
```
input_data_scaled = scaler.transform([random_values20])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [635]:
```
input_data_scaled = scaler.transform([random_values21])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [636]:
```
input_data_scaled = scaler.transform([random_values22])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [637]:
```
input_data_scaled = scaler.transform([random_values23])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

In [638]:
```
input_data_scaled = scaler.transform([random_values24])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [639]:
```
input_data_scaled = scaler.transform([random_values25])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [640]:
```
input_data_scaled = scaler.transform([random_values26])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [641]:
```
input_data_scaled = scaler.transform([random_values27])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Moderate
```

In [642]:
```
input_data_scaled = scaler.transform([random_values28])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Normal
```

In [643]:
```
input_data_scaled = scaler.transform([random_values29])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Mild
```

In [644]:
```
input_data_scaled = scaler.transform([random_values30])
prediction = svm_stress.predict(input_data_scaled)
print("Prediction:", prediction[0])
```

```
Prediction: Severe
```

(5) Saving Models

Saving Model of Preprocessing

In [ ]:
```
scaler_path = "/saved_models/scaler.h5"
with open(scaler_path, 'wb') as file:
    pickle.dump(scaler_path, file)
```

In [ ]:
```
scaler_path_model = "/saved_models/svm_stress_model.pkl"
loaded_model = pickle.load(open(scaler_path_model, 'rb'))
```

Saving Model of Depression

In [645]:
```
svm_model_path = "/saved_models/svm_depression_model.pkl"
with open(svm_model_path, 'wb') as file:
    pickle.dump(svm_depression, file)
```

In [646]:
```
svm_model_path_depression = "/saved_models/svm_depression_model.pkl"
depression_model = pickle.load(open(svm_model_path_depression, 'rb'))
```

In [647]:
```
input_data_Normal = [0, 2, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 7, 6, 4, 5,
input_data_scaled = scaler.transform([input_data_Normal])
```

In [648]:
```
predict = depression_model.predict(input_data_scaled)
print(predict)
```

```
['Normal']
```

Saving a Model of Anxiety

In [649]:
```
svm_model_path = "/saved_models/svm_anxity_model.pkl"
with open(svm_model_path, 'wb') as file:
    pickle.dump(svm_anxity, file)
```

In [650]:
```
svm_model_path_anxiety = "/saved_models/svm_anxity_model.pkl"
anxiety_model = pickle.load(open(svm_model_path_anxiety, 'rb'))
```

In [651]:
```
input_data_Extremely_Severe = [1, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 2
input_data_scaled = scaler.transform([input_data_Extremely_Severe])
```

In [652]:
```
predict = anxiety_model.predict(input_data_scaled)
print(predict)
```

```
['Extremely Severe']
```

Saving a Model of Stress

In [653]:
```
svm_model_path = "/saved_models/svm_stress_model.pkl"
with open(svm_model_path, 'wb') as file:
    pickle.dump(svm_stress, file)
```

In [654]:
```
svm_model_path_stress = "/saved_models/svm_stress_model.pkl"
stress_model = pickle.load(open(svm_model_path_stress, 'rb'))
```

In [655]:
```
input_data_Mild = [1, 2, 1, 1, 0, 3, 0, 0, 3, 2, 0, 1, 0, 2, 1, 1, 7, 4, 6
input_data_scaled = scaler.transform([input_data_Mild])
```

In [656]:
```
predict = loaded_model.predict(input_data_scaled)
print(predict)
```

```
['Mild']
```

Saved Models Working Well 👌

(6) Refrences

1- Mental_health_of_youth_ML_model (https://github.com/Dextroxe/Mental_health_of_youth_ML_model/tree/main)

2- Indian Youth Mental Health (https://docs.google.com/forms/d/e/1FAIpQLSf9tiCdI0N_2yX9lVnfaa_pd8oVhmbaISDMWWCTtLz

3- The DASS-42 is designed to measure the emotional states of depression, anxiety and stress. (https://github.com/SabbirHosen/DAS_42)

4- Depression Anxiety Stress Scales Responses (https://github.com/SabbirHosen/DAS_42)

5- Depression Classification [EDA + 97% SVC acc] (https://www.kaggle.com/code/ammarsayedtaha/depression-classification-eda-97-svc-acc)

6- DAS PREDICTION (https://www.kaggle.com/code/teju4405/das-prediction?scriptVersionId=92631082&cellId=9)

7- TIPIs Questions (https://www.psytoolkit.org/cgi-bin/3.4.4/survey?s=7rOq6)

متنساش تصلي على النبي ❤️
