Importing Libraries

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

```
import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px

from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Loading Dataset

```
pd.set_option('display.max_columns', None)
burnoutDf=pd.read_csv('/content/drive/MyDrive/burnout.csv')
burnoutDf
```

	Employee ID	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score
0	fffe31003300390039003000	10-12-2008	Female	Service	No	2	5	7.7
1	fffe31003300310037003800	14-08-2008	Female	Product	Yes	1	2	5.2
2	fffe33003400380035003900	13-11-2008	Male	Product	Yes	1	3	5.9
3	fffe3100370039003200	07-02-2008	Female	Service	No	3	6	4.6
4	fffe32003600390036003700	17-07-2008	Female	Product	No	2	5	6.4
...	...	...	...	...	...	...	...	...
12245	fffe3900310034003700	02-10-2008	Female	Service	Yes	1	2	6.1
12246	fffe32003600330034003000	31-03-2008	Female	Product	Yes	2	4	5.9
12247	fffe31003800340039003000	12-02-2008	Male	Service	No	4	7	9.6
12248	fffe32003600380031003800	06-02-2008	Male	Service	No	3	6	6.7
12249	fffe32003100390037003800	05-08-2008	Female	Product	No	2	2	2.0

12250 rows × 8 columns

```
# convert into dateTime dataType
burnoutDf["Date of Joining"]= pd.to_datetime(burnoutDf["Date of Joining"])
```

```
# give the number of rows and columns
burnoutDf.shape
```

```
(22750, 9)
```

```
# general information
burnoutDf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22750 entries, 0 to 22749
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Employee ID           22750 non-null  object
 1   Date of Joining       22750 non-null  datetime64[ns]
 2   Gender                22750 non-null  object
 3   Company Type          22750 non-null  object
 4   WFH Setup Available   22750 non-null  object
 5   Designation           22750 non-null  float64
 6   Resource Allocation   21369 non-null  float64
 7   Mental Fatigue Score  20633 non-null  float64
 8   Burn Rate             21626 non-null  float64
dtypes: datetime64[ns](1), float64(4), object(4)
memory usage: 1.6+ MB
```

```
# show top 5 rows
burnoutDf.head()
```

	Employee ID	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
0	fffe32003000360033003200	2008-09-30	Female	Service	No	2.0	3.0	3.8	0.16
1	fffe3700360033003500	2008-11-30	Male	Service	Yes	1.0	2.0	5.0	0.36
2	fffe31003300320037003900	2008-03-10	Female	Product	Yes	2.0	NaN	5.8	0.49
3	fffe32003400380032003900	2008-11-03	Male	Service	Yes	1.0	1.0	2.6	0.20
4	fffe31003900340031003600	2008-07-24	Female	Service	No	3.0	7.0	6.9	0.52

```
# extract all columns of the dataset
burnoutDf.columns
```

```
Index(['Employee ID', 'Date of Joining', 'Gender', 'Company Type',
       'WFH Setup Available', 'Designation', 'Resource Allocation',
       'Mental Fatigue Score', 'Burn Rate'],
      dtype='object')
```

```
#check for null values
burnoutDf.isna().sum()
```

```
Employee ID                0
Date of Joining            0
Gender                     0
Company Type               0
WFH Setup Available        0
Designation                0
Resource Allocation     1381
Mental Fatigue Score    2117
Burn Rate               1124
dtype: int64
```

```
# check the duplicate values
burnoutDf.duplicated().sum()
```

```
0
```

```
# calculate the mean , std, min, max and count of every attributes
burnoutDf.describe()
```

	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
count	22750.000000	21369.000000	20633.000000	21626.000000
mean	2.178725	4.481398	5.728188	0.452005
std	1.135145	2.047211	1.920839	0.198226
min	0.000000	1.000000	0.000000	0.000000
25%	1.000000	3.000000	4.600000	0.310000
50%	2.000000	4.000000	5.900000	0.450000
75%	3.000000	6.000000	7.100000	0.590000
max	5.000000	10.000000	10.000000	1.000000

```
# show the unique values
for i, col in enumerate(burnoutDf.columns):
  print(f"\n\n{burnoutDf[col].unique()}")
  print(f"\n{burnoutDf[col].value_counts()}\n\n")
```

```
['fffe32003000360033003200' 'fffe3700360033003500'
 'fffe31003300320037003900' ... 'fffe390032003000'
 'fffe33003300320036003900' 'fffe3400350031003800']

fffe32003000360033003200    1
fffe3600360035003500        1
fffe3800360034003400        1
fffe31003000310033003600    1
fffe31003400350031003700    1
                           ..
fffe33003400340032003400    1
fffe32003100370036003600    1
fffe31003900310035003800    1
fffe32003400320034003200    1
fffe3400350031003800        1
Name: Employee ID, Length: 22750, dtype: int64



['2008-09-30T00:00:00.000000000' '2008-11-30T00:00:00.000000000'
 '2008-03-10T00:00:00.000000000' '2008-11-03T00:00:00.000000000'
 '2008-07-24T00:00:00.000000000' '2008-11-26T00:00:00.000000000'
 '2008-01-02T00:00:00.000000000' '2008-10-31T00:00:00.000000000'
 '2008-12-27T00:00:00.000000000' '2008-03-09T00:00:00.000000000'
 '2008-03-16T00:00:00.000000000' '2008-05-12T00:00:00.000000000'
 '2008-01-20T00:00:00.000000000' '2008-02-23T00:00:00.000000000'
 '2008-05-14T00:00:00.000000000' '2008-02-03T00:00:00.000000000'
 '2008-03-17T00:00:00.000000000' '2008-03-28T00:00:00.000000000'
 '2008-05-29T00:00:00.000000000' '2008-06-27T00:00:00.000000000'
 '2008-08-31T00:00:00.000000000' '2008-01-15T00:00:00.000000000'
 '2008-05-04T00:00:00.000000000' '2008-11-17T00:00:00.000000000'
 '2008-09-14T00:00:00.000000000' '2008-10-09T00:00:00.000000000'
```

```
 '2008-09-14T00:00:00.000000000' '2008-10-09T00:00:00.000000000'
 '2008-10-11T00:00:00.000000000' '2008-09-18T00:00:00.000000000'
 '2008-09-16T00:00:00.000000000' '2008-12-16T00:00:00.000000000'
 '2008-05-03T00:00:00.000000000' '2008-08-04T00:00:00.000000000'
 '2008-07-31T00:00:00.000000000' '2008-06-17T00:00:00.000000000'
 '2008-04-28T00:00:00.000000000' '2008-10-30T00:00:00.000000000'
 '2008-02-27T00:00:00.000000000' '2008-06-22T00:00:00.000000000'
 '2008-02-18T00:00:00.000000000' '2008-06-24T00:00:00.000000000'
 '2008-12-08T00:00:00.000000000' '2008-08-05T00:00:00.000000000'
 '2008-04-11T00:00:00.000000000' '2008-03-26T00:00:00.000000000'
 '2008-08-09T00:00:00.000000000' '2008-08-28T00:00:00.000000000'
 '2008-03-21T00:00:00.000000000' '2008-07-22T00:00:00.000000000'
 '2008-05-20T00:00:00.000000000' '2008-01-23T00:00:00.000000000'
 '2008-09-10T00:00:00.000000000' '2008-05-26T00:00:00.000000000'
 '2008-12-22T00:00:00.000000000' '2008-04-08T00:00:00.000000000'
 '2008-02-25T00:00:00.000000000' '2008-04-24T00:00:00.000000000'
 '2008-01-08T00:00:00.000000000' '2008-11-20T00:00:00.000000000'
 '2008-09-11T00:00:00.000000000' '2008-06-11T00:00:00.000000000'
 '2008-02-28T00:00:00.000000000' '2008-08-20T00:00:00.000000000'
 '2008-10-18T00:00:00.000000000' '2008-08-14T00:00:00.000000000'
 '2008-07-17T00:00:00.000000000' '2008-07-05T00:00:00.000000000'
 '2008-02-04T00:00:00.000000000' '2008-08-01T00:00:00.000000000'
 '2008-05-01T00:00:00.000000000' '2008-05-21T00:00:00.000000000'
 '2008-10-21T00:00:00.000000000' '2008-03-19T00:00:00.000000000'
```

```
# Drop irrelevant column
burnoutDf=burnoutDf.drop(['Employee ID'],axis=1)
```

```
# check the skewness of the attributes
intFloatburnoutDf=burnoutDf.select_dtypes([np.int, np.float])
for i, col in enumerate(intFloatburnoutDf.columns):
  if (intFloatburnoutDf[col].skew() >= 0.1):
    print("\n",col, "feature is Positively Skewed and value is: ", intFloatburnoutDf[col].skew())
  elif (intFloatburnoutDf[col].skew() <= -0.1):
      print("\n",col, "feature is Negatively Skewed and value is: ", intFloatburnoutDf[col].skew())
  else:
        print("\n",col, "feature is Normally Distributed and value is: ", intFloatburnoutDf[col].skew())
```

```
 Designation feature is Normally Distributed and value is:  0.09242138478903683

 Resource Allocation feature is Positively Skewed and value is:  0.20457273454318103

 Mental Fatigue Score feature is Negatively Skewed and value is:  -0.4308950578815428

 Burn Rate feature is Normally Distributed and value is:  0.045737370909640515
```

```
# Replace the null values with mean
burnoutDf['Resource Allocation'].fillna(burnoutDf['Resource Allocation'].mean(),inplace=True)
burnoutDf['Mental Fatigue Score'].fillna(burnoutDf['Mental Fatigue Score'].mean(),inplace=True)
burnoutDf['Burn Rate'].fillna(burnoutDf['Burn Rate'].mean(),inplace=True)
```

```
# check for null values
burnoutDf.isna().sum()
```

```
Date of Joining         0
Gender                  0
Company Type            0
WFH Setup Available     0
Designation             0
Resource Allocation     0
```

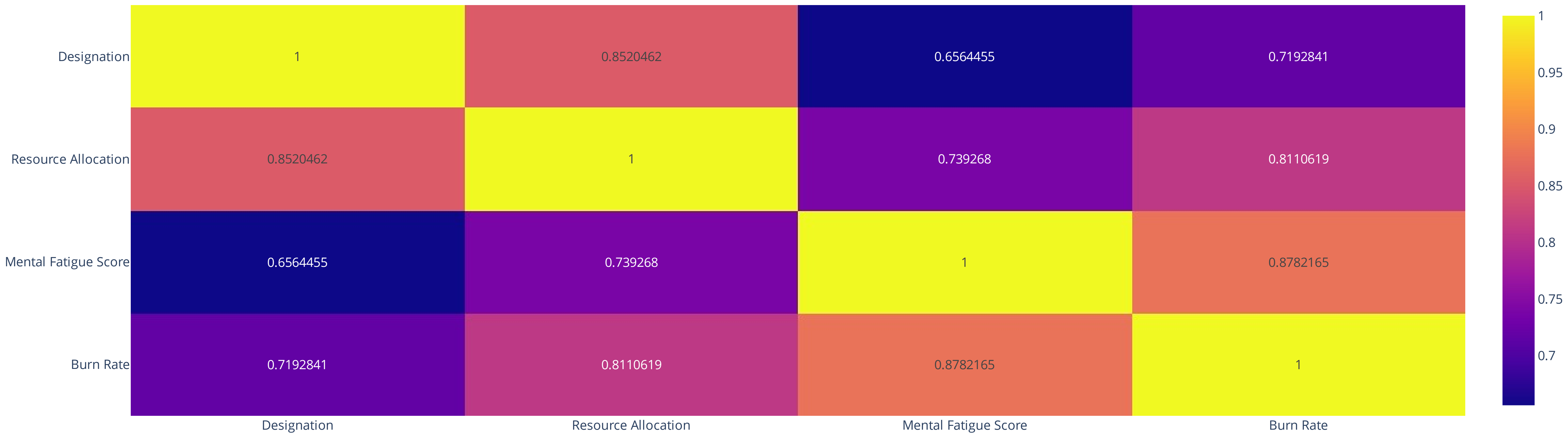
```
Resource Allocation      0
Mental Fatigue Score     0
Burn Rate                0
dtype: int64
```

```
# show the correlation
burnoutDf.corr()
```

	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
Designation	1.000000	0.852046	0.656445	0.719284
Resource Allocation	0.852046	1.000000	0.739268	0.811062
Mental Fatigue Score	0.656445	0.739268	1.000000	0.878217
Burn Rate	0.719284	0.811062	0.878217	1.000000

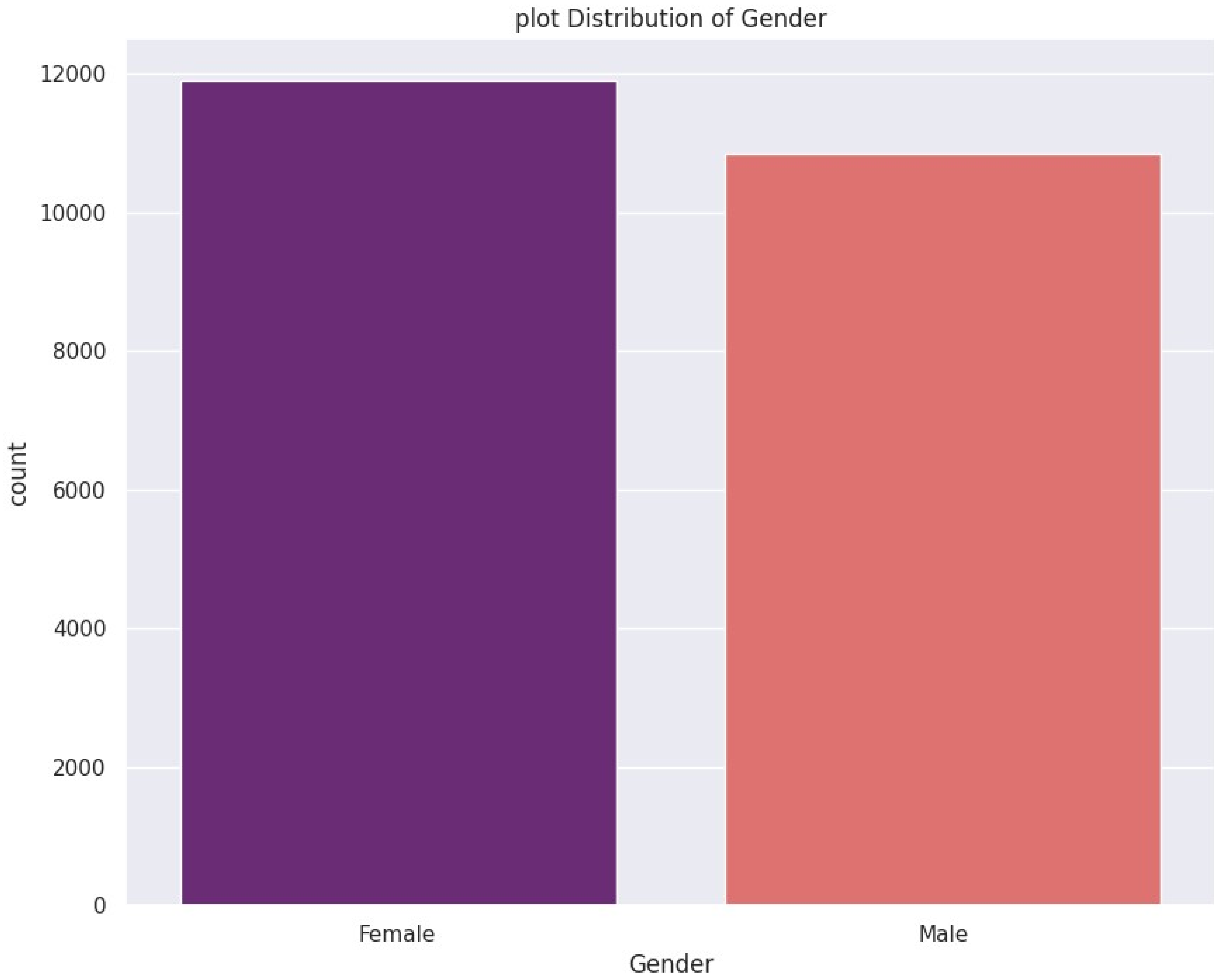
Data Visualization

```
# Plotting Heat map to check correlation
corr=burnoutDf.corr()
sns.set(rc={'figure.figsize':(14,12)})
fig = px.imshow(corr, text_auto=True, aspect="auto")
fig.show()
```

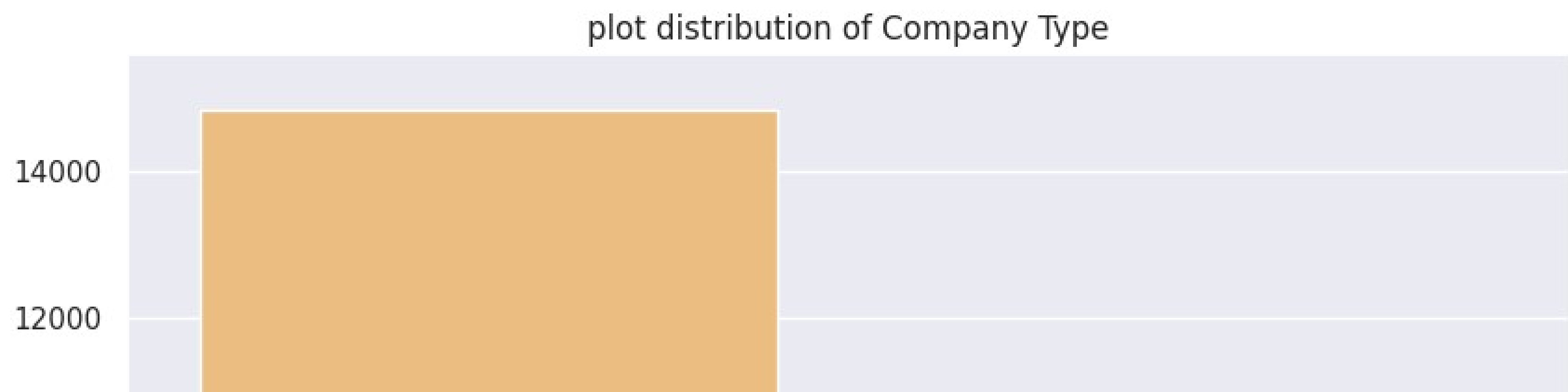


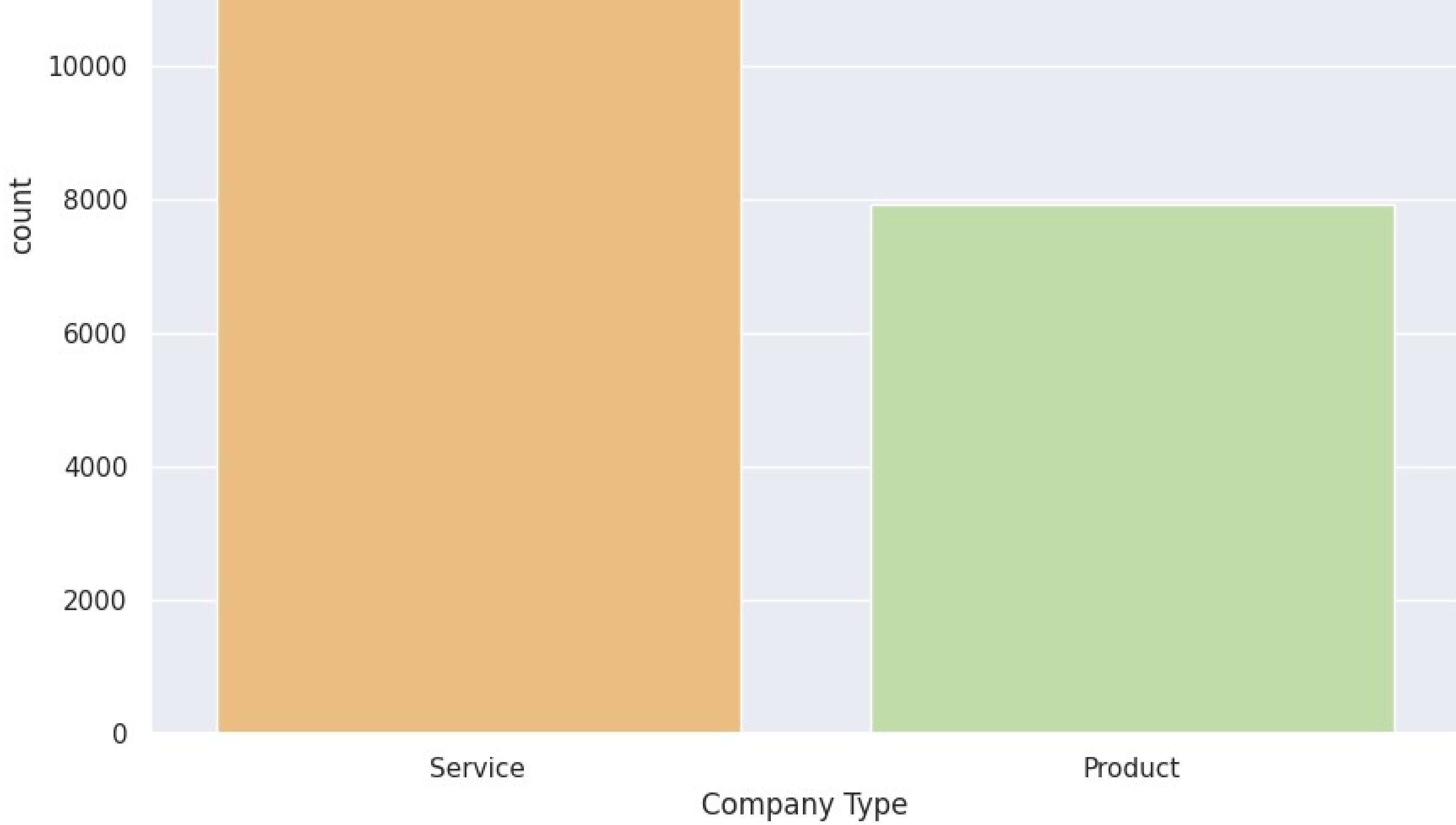

```
# Count plot Distribution of "Gender"
plt.figure(figsize=(10,8))
sns.countplot(x="Gender", data=burnoutDf, palette="magma")
```

```
plt.title("plot Distribution of Gender")
plt.show()
```

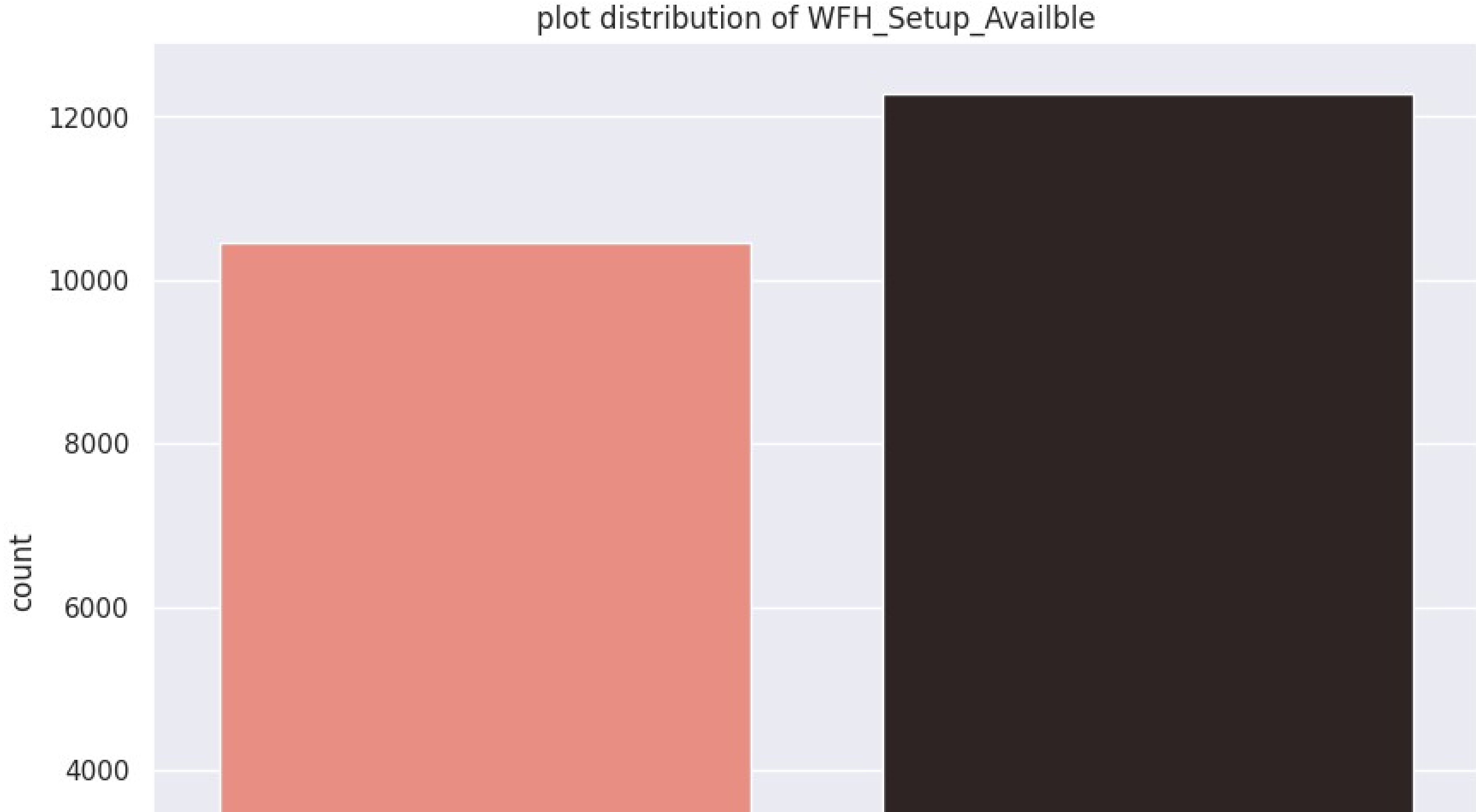



```
# Count plot distribution of "Company Type"
plt.figure(figsize=(10,8))
sns.countplot(x="Company Type", data=burnoutDf, palette="Spectral")
plt.title("plot distribution of Company Type")
plt.show()
```

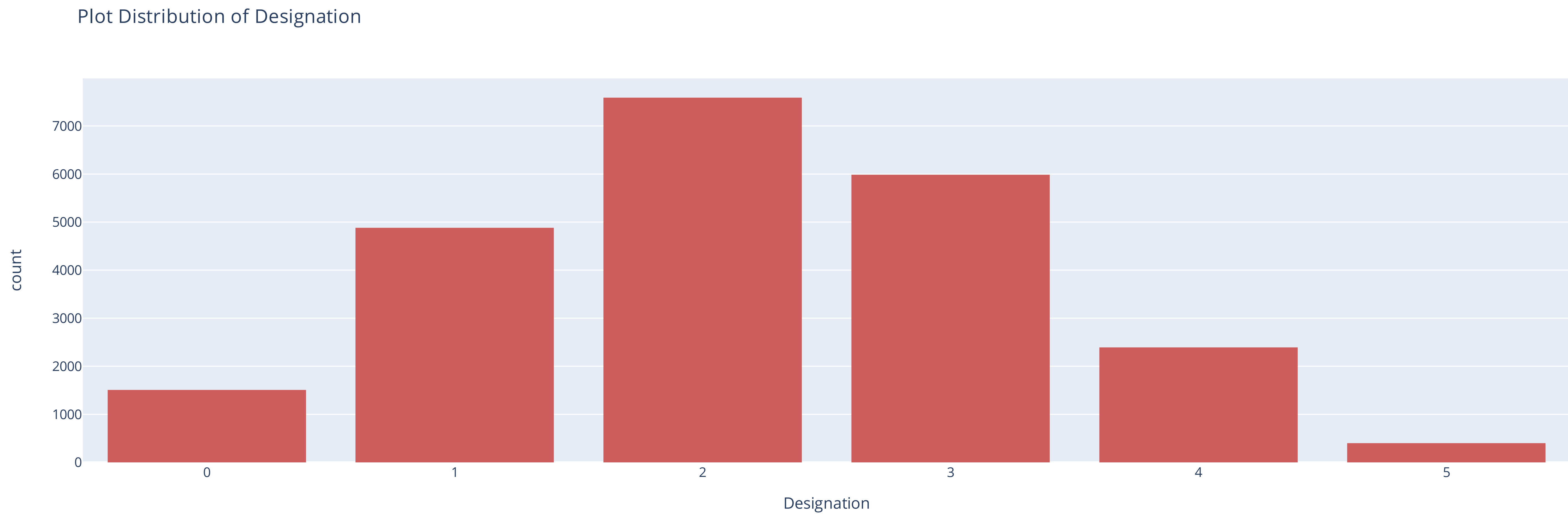


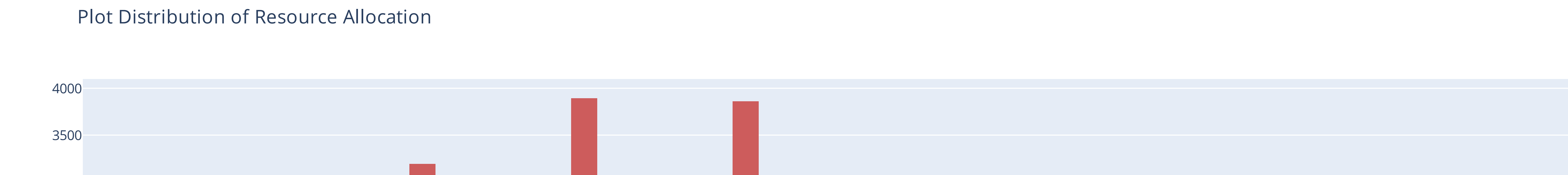


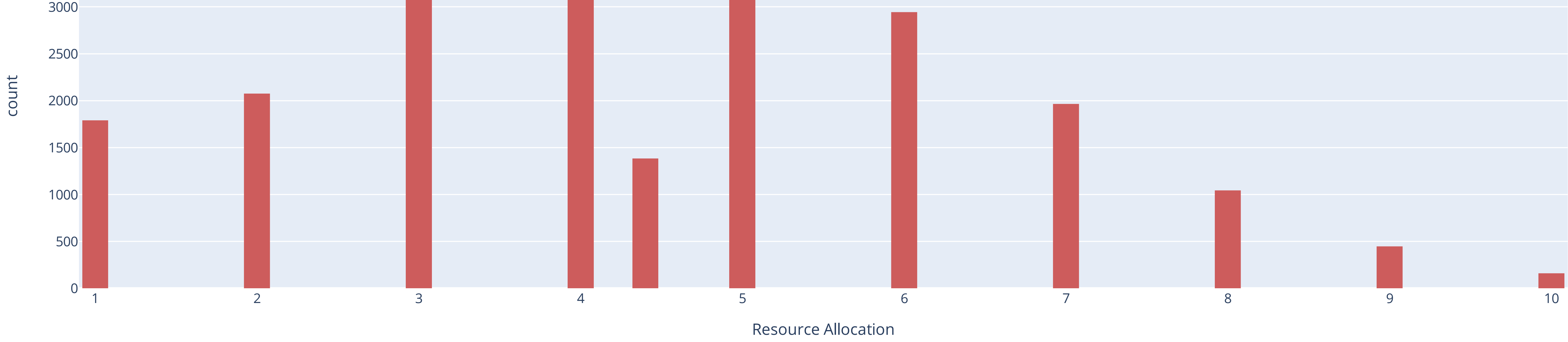

```
# Count plot distribution of "WFH Setup Available"
plt.figure(figsize=(10,8))
sns.countplot(x="WFH Setup Available", data=burnoutDf, palette="dark:salmon_r")
plt.title("plot distribution of WFH_Setup_Availble")
plt.show()
```



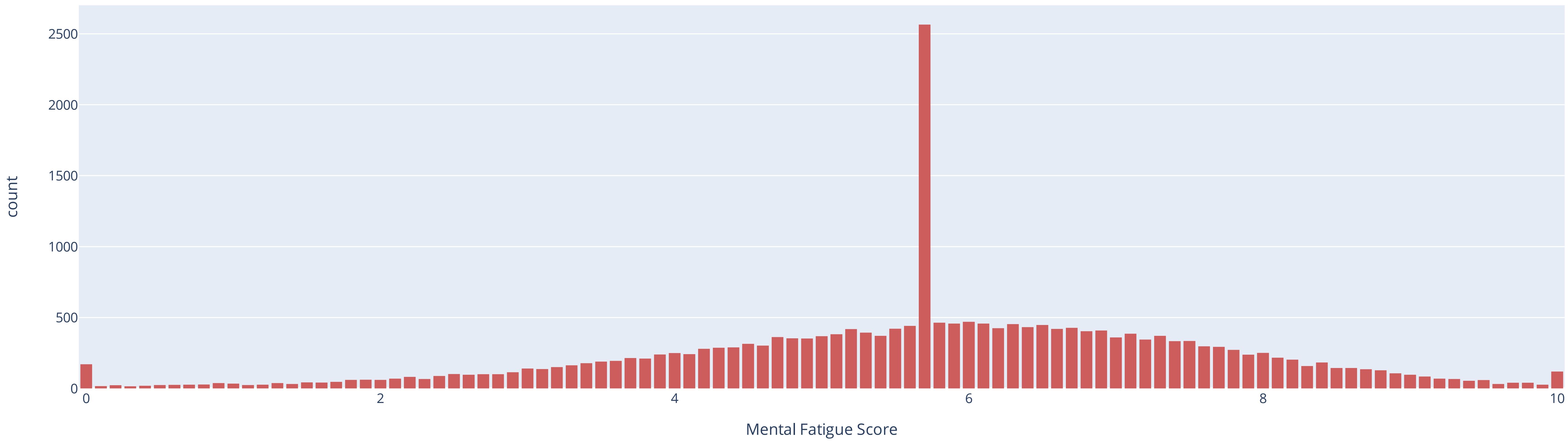

```
# Count-plot diaatribution of attributes with the help of Histogram
burn_st=burnoutDf.loc[:,'Date of Joining':'Burn Rate']
burn_st=burn_st.select_dtypes([int, float])
for i, col in enumerate(burn_st.columns):
    fig = px.histogram(burn_st, x=col, title="Plot Distribution of "+col, color_discrete_sequence=['indianred'])
    fig.update_layout(bargap=0.2)
    fig.show()
```



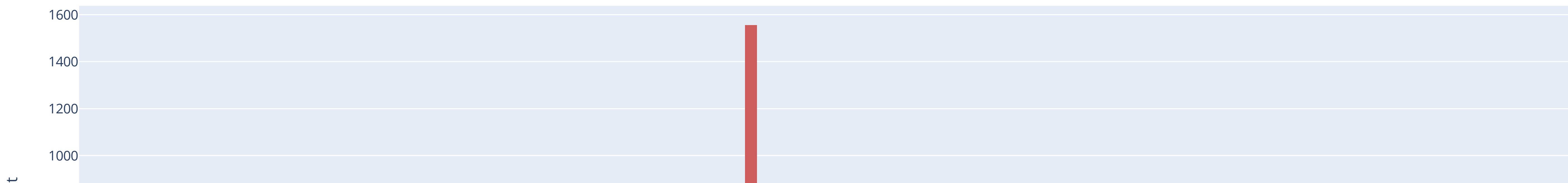




Plot Distribution of Mental Fatigue Score

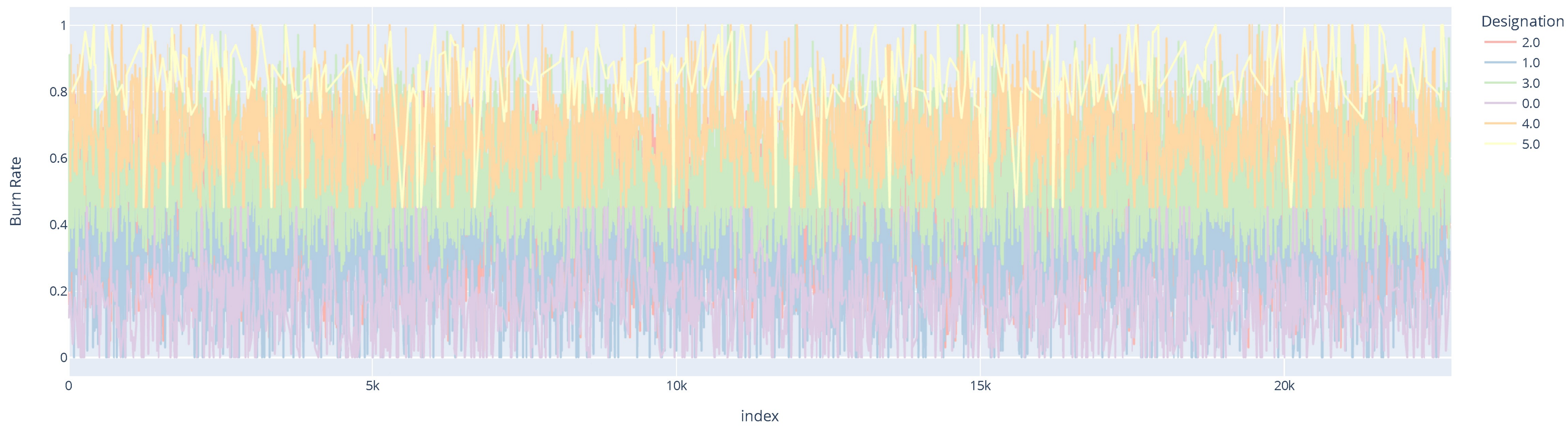


Plot Distribution of Burn Rate



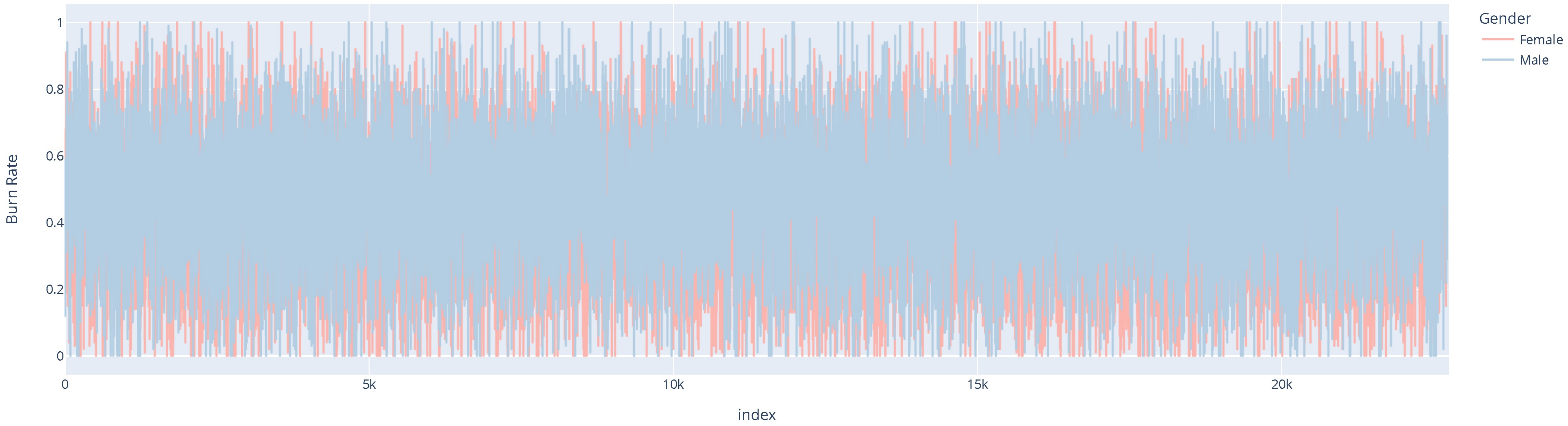

```
# Plot distribution of Burn rate on the basis of Designation
fig = px.line(burnoutDf, y="Burn Rate", color="Designation", title="Burn rate on the basis of Designation",color_discrete_sequence=px.colors.qualitative.Pastel1)
fig.update_layout(bargap=0.1)
fig.show()
```

Burn rate on the basis of Designation

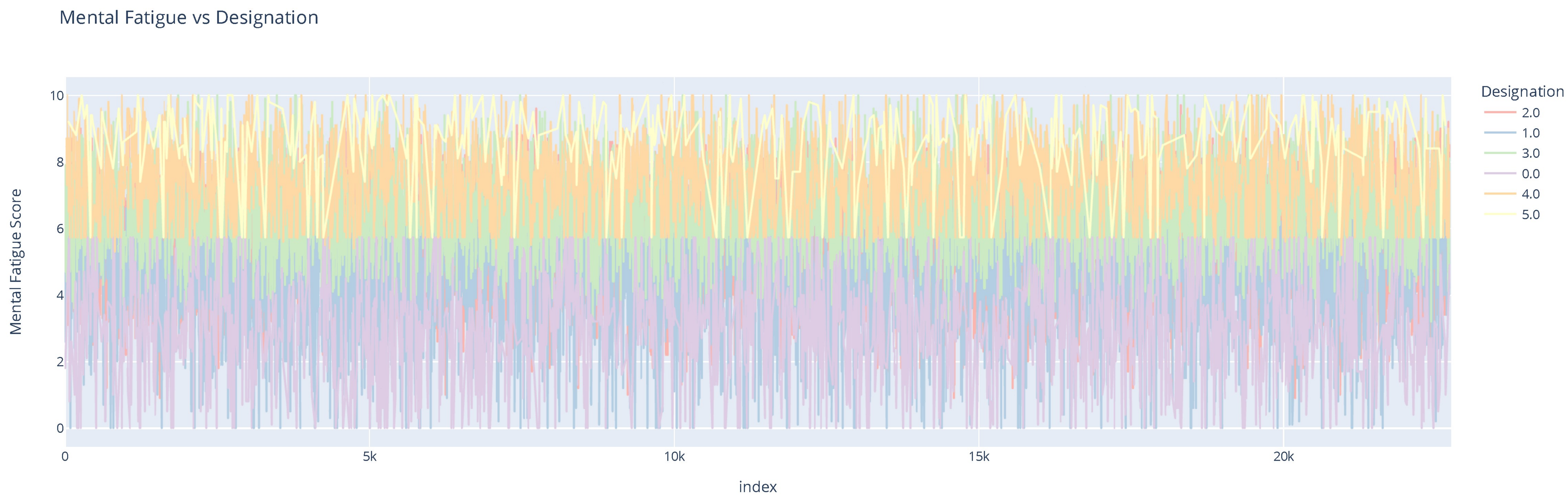



```
# Plot distribution of Burn Rate on the basis of Gender
fig = px.line(burnoutDf, y="Burn Rate", color="Gender", title="Burn Rate on the basis of Gender",color_discrete_sequence=px.colors.qualitative.Pastel1)
fig.update_layout(bargap=0.2)
fig.show()
```

Burn Rate on the basis of Gender




```
# Plot distribution of mental fatigue score on the basis of Designation
fig = px.line(burnoutDf, y="Mental Fatigue Score", color="Designation", title="Mental Fatigue vs Designation",color_discrete_sequence=px.colors.qualitative.Pastel1)
fig.update_layout(bargap=0.2)
fig.show()
```



```
# plot distribution of "Designation vs mental fatigue"as per Company type , Burn rate and Gender
sns.relplot(
    data=burnoutDf, x="Designation", y="Mental Fatigue Score", col="Company Type",
    hue="Company Type", size="Burn Rate", style="Gender",
    palette=["g", "r"], sizes=(50, 200)
)
```

```
<seaborn.axisgrid.FacetGrid at 0x7ffaf00a8430>
```

Label Encoding

```
# label encoding and assign in new variable
from sklearn import preprocessing
Lable_encode = preprocessing.LabelEncoder()
```

```
# assign in new variable
burnoutDf['GenderLable'] = Lable_encode.fit_transform(burnoutDf['Gender'].values)
burnoutDf['Company_TypeLable'] = Lable_encode.fit_transform(burnoutDf['Company Type'].values)
burnoutDf['WFH_Setup_AvailableLable'] = Lable_encode.fit_transform(burnoutDf['WFH Setup Available'].values)
```

```
# check assigned values
gn = burnoutDf.groupby('Gender')
gn = gn['GenderLable']
gn.first()
```

```
Gender
Female    0
Male      1
Name: GenderLable, dtype: int64
```

```
# check assigned values
ct = burnoutDf.groupby('Company Type')
ct = ct['Compant_TypeLabel']
ct.first()
```

```
Company Type
Product    0
Service    1
Name: Compant_TypeLabel, dtype: int64
```

```
# check assigned values
wsa = burnoutDf.groupby('WFH Setup Available')
wsa = wsa['WFH_Setup_AvailableLable']
wsa.first()
```

```
WFH Setup Available
No     0
Yes    1
Name: WFH_Setup_AvailableLable, dtype: int64
```

```
# show last 10 rows
burnoutDf.tail(10)
```

	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate	GenderLable	Compant_TypeLable	GenderLabel	Compant_TypeLabel	Company_TypeLable	WFH_Setup_AvailableL
22740	2008-09-05	Female	Product	No	3.0	6.0	7.300000	0.550000	0	0	0	0	0	
22741	2008-01-07	Male	Product	No	2.0	5.0	6.000000	0.452005	1	0	1	0	0	
22742	2008-07-28	Male	Product	No	3.0	5.0	8.100000	0.690000	1	0	1	0	0	
22743	2008-12-15	Female	Product	Yes	1.0	3.0	6.000000	0.480000	0	0	0	0	0	
22744	2008-05-27	Male	Product	No	3.0	7.0	6.200000	0.540000	1	0	1	0	0	
22745	2008-12-30	Female	Service	No	1.0	3.0	5.728188	0.410000	0	1	0	1	1	
22746	2008-01-19	Female	Product	Yes	3.0	6.0	6.700000	0.590000	0	0	0	0	0	
22747	2008-11-05	Male	Service	Yes	3.0	7.0	5.728188	0.720000	1	1	1	1	1	
22748	2008-01-10	Female	Service	No	2.0	5.0	5.900000	0.520000	0	1	0	1	1	
22749	2008-01-06	Male	Product	No	3.0	6.0	7.800000	0.610000	1	0	1	0	0	

Feature Selection

```
# feature selection
columns=['Designation', 'Resource Allocation', 'Mental Fatigue Score',
       'GenderLable', 'Company_TypeLable', 'WFH_Setup_Available']
x=burnoutDf[columns]
y=burnoutDf['Burn Rate']
```

```
print(x)
```

```
       Designation  Resource Allocation  Mental Fatigue Score  GenderLable  \
```

```
       Designation  Resource Allocation  Mental Fatigue Score  GenderLable  \
0              2.0             3.000000              3.800000            0
1              1.0             2.000000              5.000000            1
2              2.0             4.481398              5.800000            0
3              1.0             1.000000              2.600000            1
4              3.0             7.000000              6.900000            0
...            ...                  ...                   ...          ...
22745          1.0             3.000000              5.728188            0
22746          3.0             6.000000              6.700000            0
22747          3.0             7.000000              5.728188            1
22748          2.0             5.000000              5.900000            0
22749          3.0             6.000000              7.800000            1

       Company_TypeLable
0                      1
1                      1
2                      0
3                      1
4                      1
...                  ...
22745                  1
22746                  0
22747                  1
22748                  1
22749                  0

[22750 rows x 5 columns]
```

```
print(y)
```

```
0        0.16
1        0.36
2        0.49
3        0.20
4        0.52
         ...
22745    0.41
22746    0.59
22747    0.72
22748    0.52
22749    0.61
Name: Burn Rate, Length: 22750, dtype: float64
```

Implementing PCA

```
# principle component analysis
from sklearn.decomposition import PCA
pca = PCA(0.95)
x_pca = pca.fit_transform(x)
print("PCA shaoe of x is: ",x_pca.shape, "and original shape is: ", x.shape)
print("% of importance of selected features is:", pca.explained_variance_ratio_)
print("The number of features selected through PCA is:", pca.n_components_)
```

```
PCA shaoe of x is:  (22750, 4) and original shape is:  (22750, 5)
% of importance of selected features is: [0.80288084 0.11418113 0.03102338 0.0268774 ]
The number of features selected through PCA is: 4
```

Data Splitting

```
# Data Splitting in train and test
from sklearn.model_selection import train_test_split
x_train_pca, x_test, v_train, v_test = train_test_split(x_pca,y, test_size = 0.25, random_state=10)
```

```
# print the shape of splitted data
print(x_train_pca.shape, x_test.shape, v_train.shape, v_test.shape)
```

```
(17062, 4) (5688, 4) (17062,) (5688,)
```

MODEL IMPLEMENTATION

Random Forest Regressor

```
from sklearn.metrics import r2_score
```

```
# Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor

rf_model = RandomForestRegressor()
rf_model.fit(x_train_pca, v_train)

train_pred_rf = rf_model.predict(x_train_pca)
train_r2 = r2_score(v_train, train_pred_rf)
test_pred_rf = rf_model.predict(x_test)
test_r2 = r2_score(v_test, test_pred_rf)
# Accuracy score
print("Accuracy score of train data: "+str(round(100*train_r2, 4))+" %")
print("Accuracy score of the test data: "+str(round(100*test_r2, 4))+" %")
```

```
Accuracy score of train data: 89.7017 %
Accuracy score of the test data: 84.4071 %
```

AdaBoost Regressor

```
# AdaBoost regressor
from sklearn.ensemble import AdaBoostRegressor
abr_model = AdaBoostRegressor()
abr_model.fit(x_train_pca, v_train)

train_pred_adboost = abr_model.predict(x_train_pca)
train_r2 = r2_score(v_train, train_pred_adboost)
test_pred_adaboost = abr_model.predict(x_test)
test_r2 = r2_score(v_test, test_pred_adaboost)

# Accuracy score
print("Accuracy score of train data: "+str(round(100*train_r2, 4))+" %")
print("Accuracy score of the test data: "+str(round(100*test_r2, 4))+" %")
```

```
Accuracy score of train data: 77.6054 %
Accuracy score of the test data: 77.2549 %
```

BURNOUT PREDICTION

```
import numpy as np
import pandas as pd

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.neighbors import KNeighborsRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.svm import LinearSVR, SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from xgboost import XGBRegressor
from lightgbm import LGBMRegressor
from sklearn.ensemble import AdaBoostRegressor

import warnings
warnings.filterwarnings(action='ignore')
```

```
burnoutDf=pd.read_csv('/content/drive/MyDrive/burnout.csv')
```

```
burnoutDf
```

	Employee ID	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
0	fffe32003000360033003200	2008-09-30	Female	Service	No	2.0	3.0	3.8	0.16
1	fffe3700360033003500	2008-11-30	Male	Service	Yes	1.0	2.0	5.0	0.36
2	fffe31003300320037003900	2008-03-10	Female	Product	Yes	2.0	NaN	5.8	0.49
3	fffe32003400380032003900	2008-11-03	Male	Service	Yes	1.0	1.0	2.6	0.20
4	fffe31003900340031003600	2008-07-24	Female	Service	No	3.0	7.0	6.9	0.52
...	...	...	...	...	...	...	...	...	...
22745	fffe31003500370039003100	2008-12-30	Female	Service	No	1.0	3.0	NaN	0.41
22746	fffe33003000350031003800	2008-01-19	Female	Product	Yes	3.0	6.0	6.7	0.59
22747	fffe390032003000	2008-11-05	Male	Service	Yes	3.0	7.0	NaN	0.72
22748	fffe33003300320036003900	2008-01-10	Female	Service	No	2.0	5.0	5.9	0.52
22749	fffe3400350031003800	2008-01-06	Male	Product	No	3.0	6.0	7.8	0.61

22750 rows × 9 columns

```
burnoutDf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22750 entries, 0 to 22749
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Employee ID           22750 non-null  object
 1   Date of Joining       22750 non-null  object
 2   Gender                22750 non-null  object
 3   Company Type          22750 non-null  object
 4   WFH Setup Available   22750 non-null  object
```

```
 4   WFH Setup Available   22750 non-null  object
 5   Designation           22750 non-null  float64
 6   Resource Allocation   21369 non-null  float64
 7   Mental Fatigue Score  20633 non-null  float64
 8   Burn Rate             21626 non-null  float64
dtypes: float64(4), object(5)
memory usage: 1.6+ MB
```

```
def preprocess_inputs(df):
    df = df.copy()

    # Drop Employee ID column
    df = df.drop('Employee ID', axis=1)

    # Drop rows with missing target values
    missing_target_rows = df.loc[df['Burn Rate'].isna(), :].index
    df = df.drop(missing_target_rows, axis=0).reset_index(drop=True)

    # Fill remaining missing values with column means
    for column in ['Resource Allocation', 'Mental Fatigue Score']:
        df[column] = df[column].fillna(df[column].mean())

    # Extract date features
    df['Date of Joining'] = pd.to_datetime(df['Date of Joining'])
    df['Join Month'] = df['Date of Joining'].apply(lambda x: x.month)
    df['Join Day'] = df['Date of Joining'].apply(lambda x: x.day)
    df = df.drop('Date of Joining', axis=1)

    # Binary encoding
    df['Gender'] = df['Gender'].replace({'Female': 0, 'Male': 1})
    df['Company Type'] = df['Company Type'].replace({'Product': 0, 'Service': 1})
    df['WFH Setup Available'] = df['WFH Setup Available'].replace({'No': 0, 'Yes': 1})

    # Split df into X and y
    y = df['Burn Rate']
    X = df.drop('Burn Rate', axis=1)

    # Train-test split
    X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, shuffle=True, random_state=1)

    # Scale X
    scaler = StandardScaler()
    scaler.fit(X_train)
    X_train = pd.DataFrame(scaler.transform(X_train), index=X_train.index, columns=X_train.columns)
    X_test = pd.DataFrame(scaler.transform(X_test), index=X_test.index, columns=X_test.columns)

    return X_train, X_test, y_train, y_test
```

```
X_train, X_test, y_train, y_test = preprocess_inputs(burnoutDf)
```

```
X_train
```

	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Join Month	Join Day
8275	-0.954022	-1.379211	-1.087295	0.725025	0.768001	0.475128	0.433442	-0.649693
21284	1.048194	0.725052	-1.087295	1.604608	1.270205	1.131455	1.596251	-0.536187
16802	1.048194	0.725052	-1.087295	-0.154557	0.768001	0.420434	1.305549	0.371860

3271	1.048194	-1.379211	-1.087295	1.604608	2.274612	1.733089	0.142739	1.620424
5302	-0.954022	-1.379211	-1.087295	-0.154557	-0.236406	0.475128	0.724144	-0.422682
...	...	...	...	...	...	...	...	...
10955	-0.954022	0.725052	-1.087295	-0.154557	0.768001	0.803292	-1.020070	-1.444234
17289	-0.954022	0.725052	0.919713	0.725025	-0.236406	-0.509363	-0.147963	0.712377
5192	-0.954022	0.725052	0.919713	0.725025	0.265797	-1.165690	1.014847	0.031342
12172	1.048194	-1.379211	0.919713	-1.913723	-1.743017	-1.220384	0.433442	-1.671246
235	-0.954022	0.725052	-1.087295	-1.913723	-1.743017	-2.861202	-0.729368	0.031342

15138 rows × 8 columns

```
y_train
```

```
8275     0.61
21284    0.81
16802    0.62
3271     0.73
5302     0.43
         ...
10955    0.58
17289    0.39
5192     0.24
12172    0.18
235      0.00
Name: Burn Rate, Length: 15138, dtype: float64
```

```
models = {
    "                     Linear Regression": LinearRegression(),
    " Linear Regression (L2 Regularization)": Ridge(),
    " Linear Regression (L1 Regularization)": Lasso(),
    "                   K-Nearest Neighbors": KNeighborsRegressor(),
    "                        Neural Network": MLPRegressor(),
    "Support Vector Machine (Linear Kernel)": LinearSVR(),
    "   Support Vector Machine (RBF Kernel)": SVR(),
    "                         Decision Tree": DecisionTreeRegressor(),
    "                         Random Forest": RandomForestRegressor(),
    "                     Gradient Boosting": GradientBoostingRegressor(),
    "                               XGBoost": XGBRegressor(),
    "                              LightGBM": LGBMRegressor(),
    "                             model_ABR":AdaBoostRegressor()
}

for name, model in models.items():
    model.fit(X_train, y_train)
    print(name + " trained.")
```

```
                     Linear Regression trained.
 Linear Regression (L2 Regularization) trained.
 Linear Regression (L1 Regularization) trained.
                   K-Nearest Neighbors trained.
                        Neural Network trained.
Support Vector Machine (Linear Kernel) trained.
   Support Vector Machine (RBF Kernel) trained.
                         Decision Tree trained.
```

```
           Random Forest trained.
       Gradient Boosting trained.
                 XGBoost trained.
                LightGBM trained.
               model_ABR trained.
```

```
for name, model in models.items():
    print(name + " R^2 Score: {:.5f}".format(model.score(X_test, y_test)))
```

```
               Linear Regression R^2 Score: 0.87075
Linear Regression (L2 Regularization) R^2 Score: 0.87075
Linear Regression (L1 Regularization) R^2 Score: -0.00001
             K-Nearest Neighbors R^2 Score: 0.85603
                  Neural Network R^2 Score: 0.86741
Support Vector Machine (Linear Kernel) R^2 Score: 0.86868
   Support Vector Machine (RBF Kernel) R^2 Score: 0.88430
                   Decision Tree R^2 Score: 0.81875
                   Random Forest R^2 Score: 0.89762
               Gradient Boosting R^2 Score: 0.90257
                         XGBoost R^2 Score: 0.90310
                        LightGBM R^2 Score: 0.90912
                       model_ABR R^2 Score: 0.81497
```