In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sb
import scipy.stats as stats
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [2]:
```
df = pd.read_csv('fake_data.csv')
```

Functions

In [3]:
```
# Detect Null's and Outliers

def data_quality(column):
    line_break = '-' * 25

    #Null's
    empty = df[column].isnull().sum()
    print(f"{line_break}\n{column}\nNumber of Null's: {empty}\n")




    if column in quantitative:
        #Outliers based on IQR
        Q1 = df[column].quantile(0.25)
        Q3 = df[column].quantile(0.75)

        IQR = Q3 - Q1

        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        # Count outliers
        IQR_outliers = ((df[column] < lower_bound) | (df[column] > upper_bou
        print(f"Number of outliers according to IQR score: {IQR_outliers}")


        #Outliers based on z-score
        df_temp = df.copy()
        df_temp['zscore'] = stats.zscore(df_temp[column])

        #count outliers
        Zscore_outliers = df_temp['zscore'].loc[(df_temp['zscore'] >= 3) | (
        print(f"Number of outliers according to z score: {Zscore_outliers}")


        #visualize
        fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(12, 6))


        sb.boxplot(y=df[column], ax=axs[0])
        sb.histplot(df[column], kde=True, ax=axs[1])

        plt.tight_layout(rect=[0, 0, 1, 0.95])
        plt.show()

    return
```

In [4]:
```
def data_summary():
    line_break = '-' * 25

    #Summary statistics of Categorical variables
    for col in categorical:
        counts = df[col].value_counts()
        percentages = (counts / counts.sum()) * 100
        print(f"{line_break}\n{col}\n{percentages}")



    #Summary statistics of Quantitative variables

    #create summary data frame
    cols = ['mean', 'median', '25%', '50%', '75%']
    summary_df = pd.DataFrame(columns=cols)
    for column in quantitative:

        #define statistics
        desc = df[column].describe()
        median = df[column].median()

        summary_data = pd.Series({
            'mean': desc['mean'],
            'median': median,
            '25%': desc['25%'],
            '50%': desc['50%'],
            '75%': desc['75%']
        }, name=column)


        # Append the summary statistics of the current variable to the summa
        summary_df = pd.concat([summary_df, summary_data.to_frame().T])

    return summary_df
```

In [5]:
```
# univariate visualization
def uni_vis(columns, title):


    count = len(columns)
    rows = int(count / 3) + (1 if count % 3 else 0)

    fig, axs = plt.subplots(rows, 3, figsize=(15,15))
    axs = axs.flatten()

    # Loop over the columns and create the plots
    for i, column in enumerate(columns):
            axs[i].hist(df[column])
            axs[i].set_title(column)
            axs[i].set_xlabel(column)
            axs[i].set_ylabel('Frequency')

    plt.tight_layout(rect=[0, 0.03, 1, 0.95])
    fig.suptitle(title, verticalalignment='top')
    plt.show()



#bivariate visualization
def bi_vis(df, y_col, x_cols, title):
    count = len(x_cols)
    rows = int(count / 3) + (1 if count % 3 else 0)

    fig, axs = plt.subplots(rows, 3, figsize=(15, rows * 5))
    axs = axs.flatten()


    # Loop over the columns and create the point plots
    for i, column in enumerate(x_cols):
        if column in categorical:
            sb.pointplot(data=df, x=column, y=y_col, ax=axs[i])
            axs[i].set_title(column)
            axs[i].set_xlabel(column)
            axs[i].set_ylabel('Total Charge')
        else:
            sb.scatterplot(data=df, x=column, y=y_col, ax=axs[i])
            axs[i].set_title(column)
            axs[i].set_xlabel(column)
            axs[i].set_ylabel('Total Charge')

    plt.tight_layout(rect=[0, 0.03, 1, 0.95])
    fig.suptitle(title, verticalalignment='top')
    plt.show()
```

In [8]:
```
# get a summary of characteristics of residuals

def residual_eval(model):
    #get residuals
    residuals = model.resid

    #calculate Residual Standard Error (RSE)
    RSE = np.sqrt((residuals**2).sum() / 9968)
    print(f'Residual Standard Error:{RSE}\n')

    #other metrics
    adjr2 = model.rsquared_adj
    AIC = model.aic
    print(f'Adjusted R-square:{adjr2}\nAIC:{AIC}')

    #Homoscedacity
    y_hat = model.predict()

    #Visualize
    sm.qqplot(residuals, line = '45', fit = True)
    plt.title('Residual test of normality')
    plt.show();

    plt.hist(residuals)
    plt.title('Residual test of normality')
    plt.xlabel('Residual')
    plt.ylabel('Count')
    plt.show();
```

Variables

In [9]:
```
target = ['CWPM']

predictors = [
              'Check-in_AM', 'Respectful_AM', 'Responsible_AM', 'Safe_AM',
               'Check-in_PM', 'Respectful_PM', 'Responsible_PM',
                'Safe_PM'
             ]

all_variables = [
                  'Check-in_AM', 'Respectful_AM', 'Responsible_AM', 'Safe_AM'
                'Check-in_PM', 'Respectful_PM', 'Responsible_PM',
                 'Safe_PM', 'CWPM'
                 ]

categorical = [
              'Check-in_AM', 'Check-in_PM'
             ]

one_hots = [
            'Check-in_AM', 'Check-in_PM'
            ]

quantitative = [ 'Respectful_AM', 'Responsible_AM', 'Safe_AM',
                 'Respectful_PM', 'Responsible_PM',
                 'Safe_PM', 'CWPM']
```

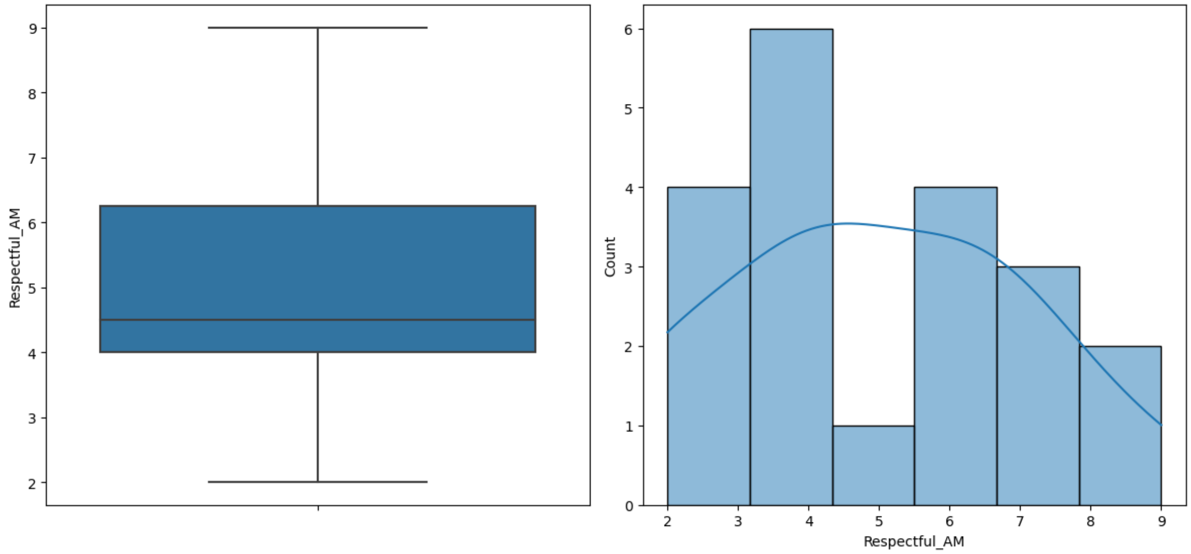
Cleaning

In [10]:
```
df.columns
```

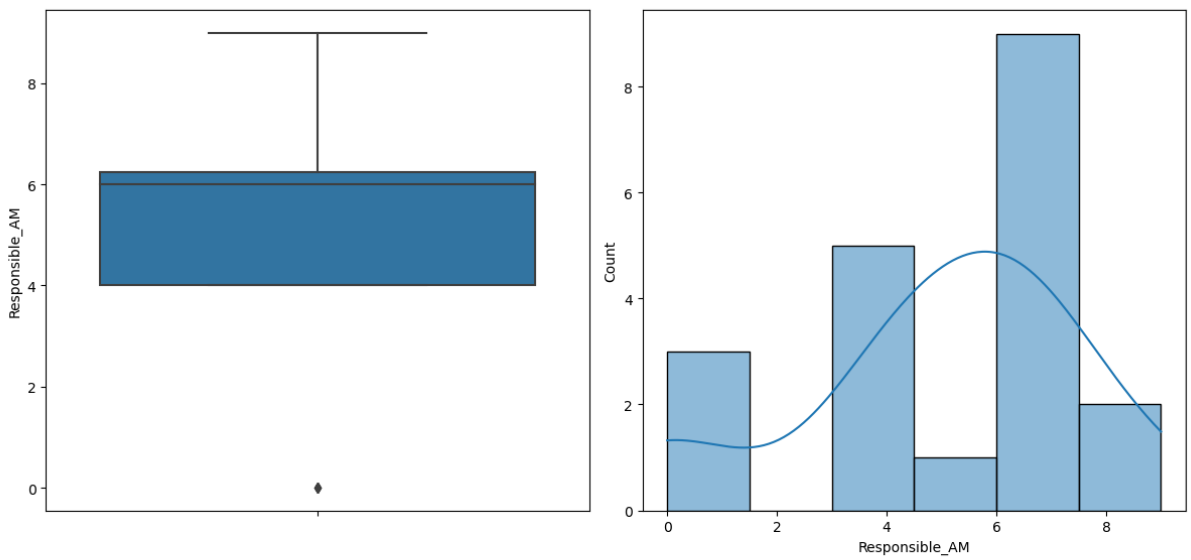
Out[10]:
```
Index(['Check-in_AM', 'Respectful_AM', 'Responsible_AM', 'Safe_AM',
       'Check-in_PM', 'Respectful_PM', 'Responsible_PM', 'Safe_PM', 'CWP
M'],
      dtype='object')
```

In [11]:
```
#assess cleaning needs
for col in all_variables:
    data_quality(col)
```

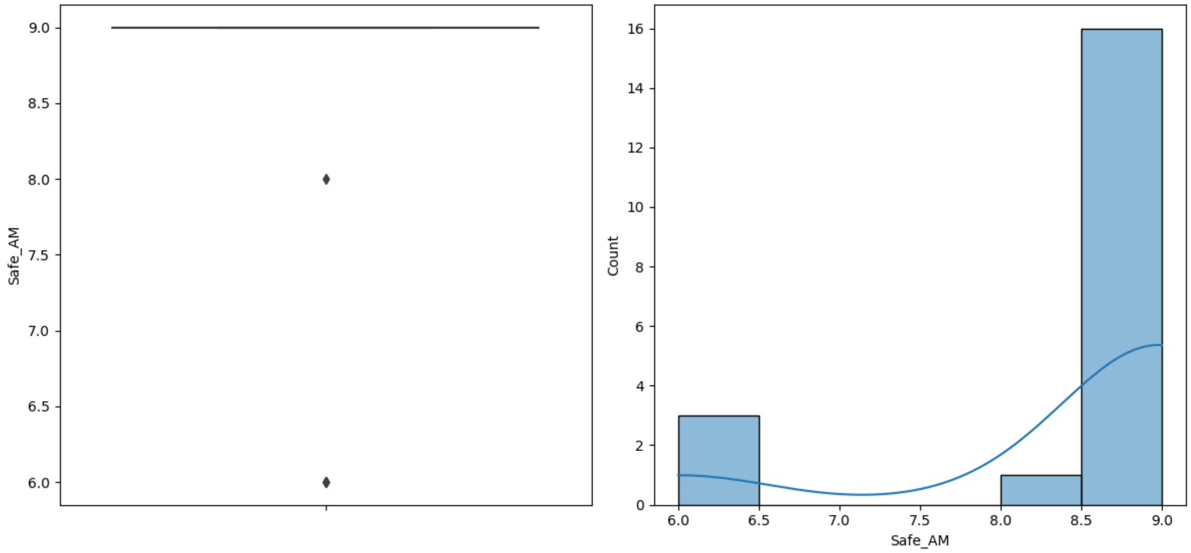
```
-------------------------
Check-in_AM
Number of Null's: 0

-------------------------
Respectful_AM
Number of Null's: 0

Number of outliers according to IQR score: 0
Number of outliers according to z score: 0
```



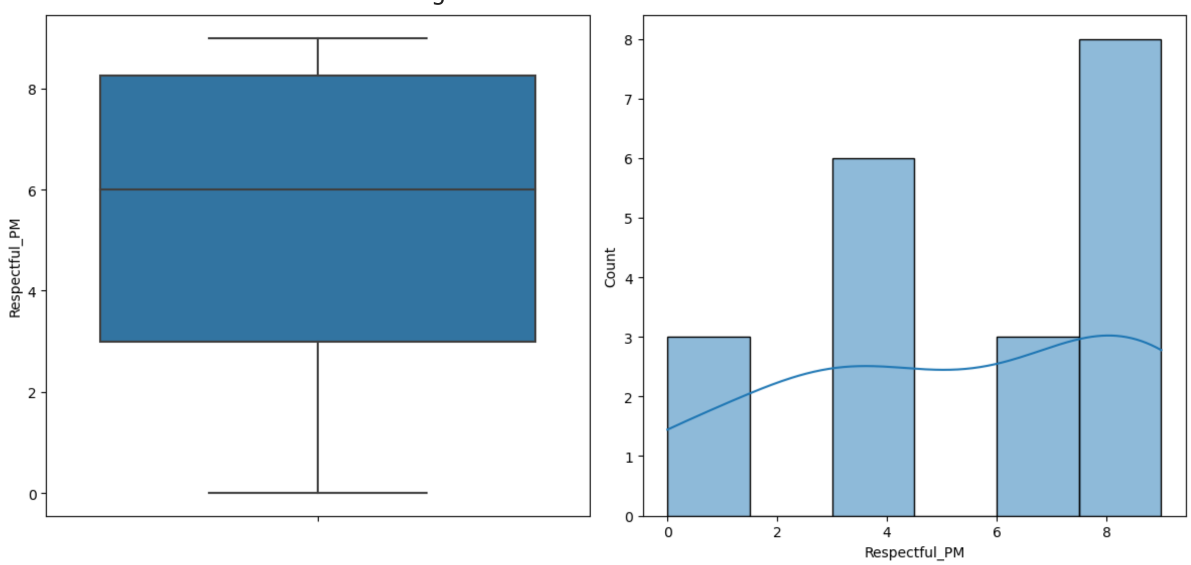

```
-------------------------
Responsible_AM
Number of Null's: 0

Number of outliers according to IQR score: 3
Number of outliers according to z score: 0
```



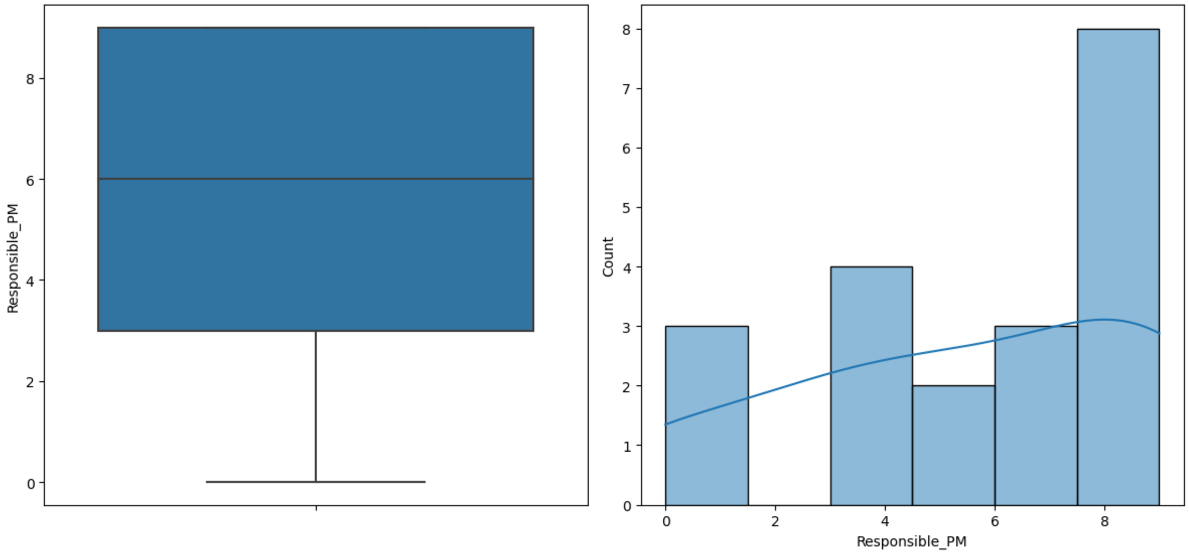

```
-------------------------
Safe_AM
Number of Null's: 0

Number of outliers according to IQR score: 4
Number of outliers according to z score: 0
```



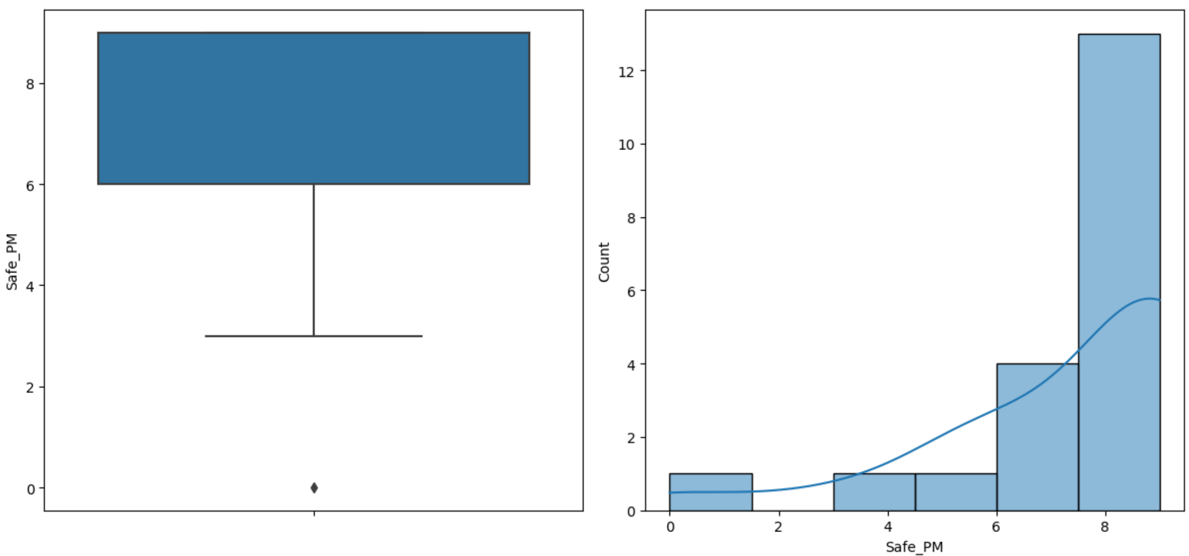

```
-------------------------
Check-in_PM
Number of Null's: 0

-------------------------
Respectful_PM
Number of Null's: 0

Number of outliers according to IQR score: 0
Number of outliers according to z score: 0
```



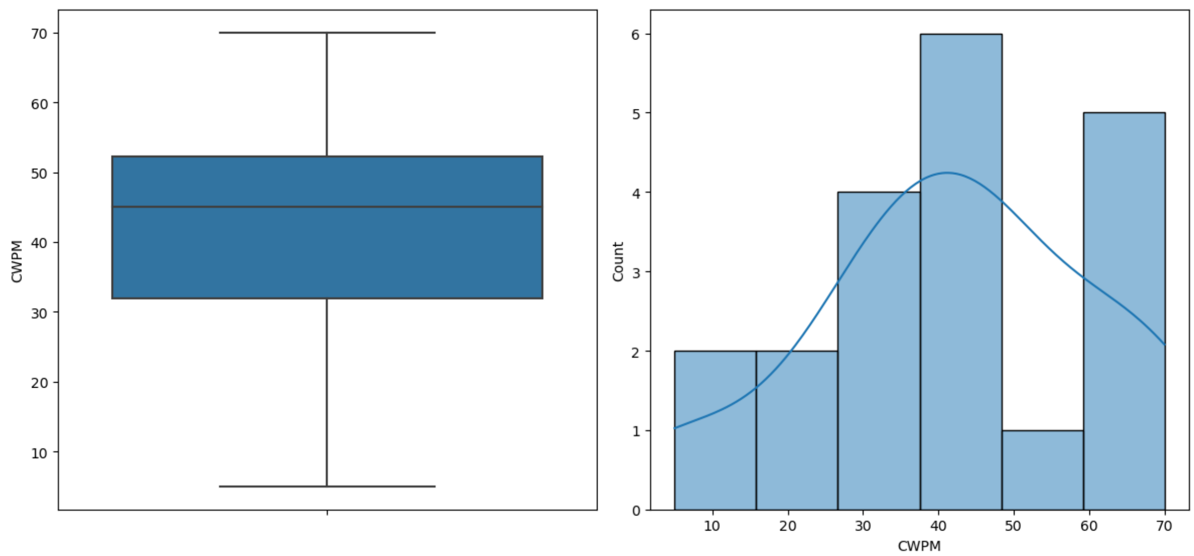

```
-------------------------
Responsible_PM
Number of Null's: 0

Number of outliers according to IQR score: 0
Number of outliers according to z score: 0
```




```
-------------------------
Safe_PM
Number of Null's: 0

Number of outliers according to IQR score: 1
Number of outliers according to z score: 1
```




```
-------------------------
CWPM
Number of Null's: 0

Number of outliers according to IQR score: 0
Number of outliers according to z score: 0
```



Treatment

Explore Summary statistics

In [12]:
```
data_summary()
```

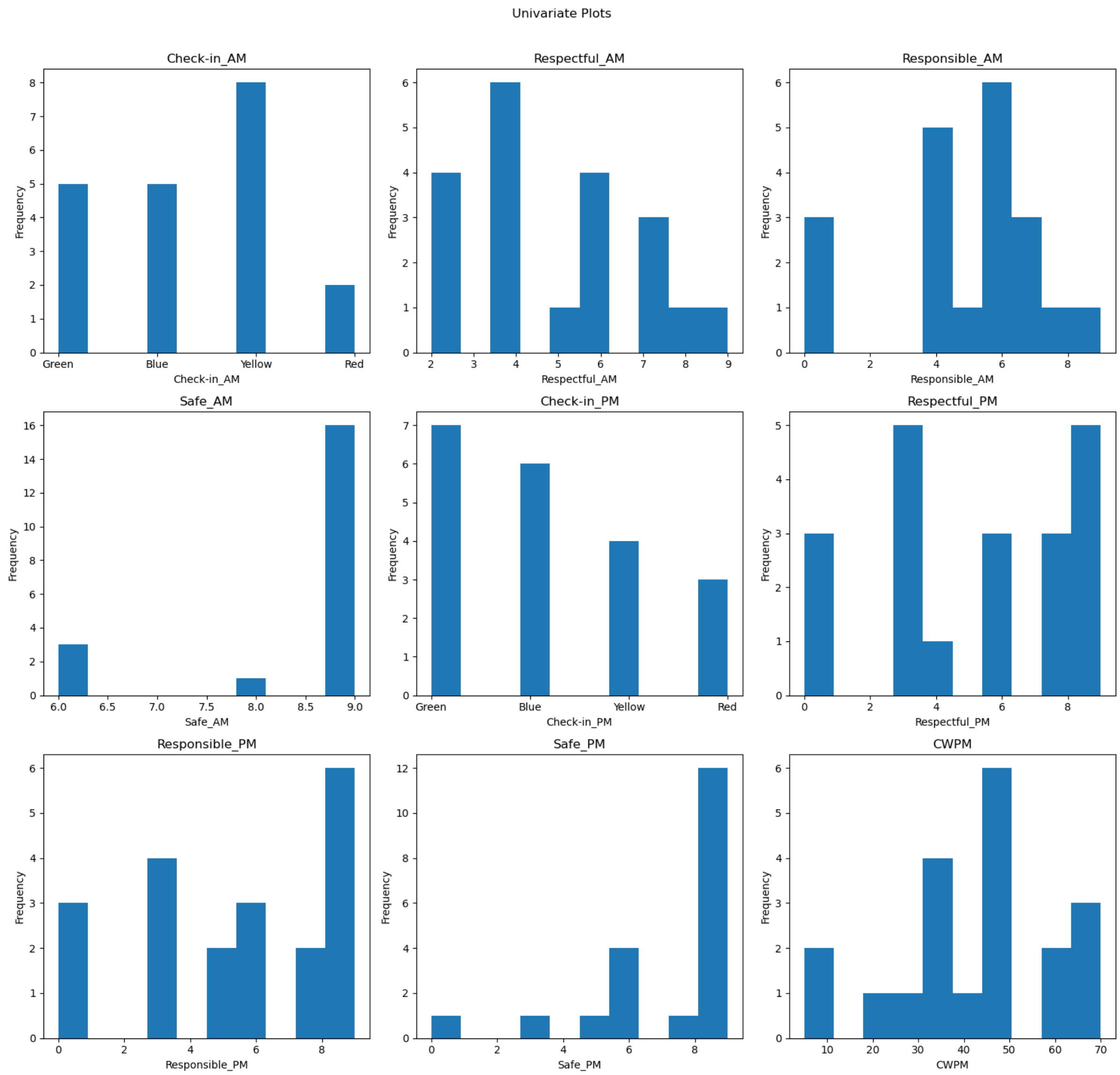
```
-------------------------
Check-in_AM
Yellow    40.0
Green     25.0
Blue      25.0
Red       10.0
Name: Check-in_AM, dtype: float64
-------------------------
Check-in_PM
Green     35.0
Blue      30.0
Yellow    20.0
Red       15.0
Name: Check-in_PM, dtype: float64
```

Out[12]:

	mean	median	25%	50%	75%
Respectful_AM	4.95	4.5	4.0	4.5	6.25
Responsible_AM	4.95	6.0	4.0	6.0	6.25
Safe_AM	8.50	9.0	9.0	9.0	9.00
Respectful_PM	5.30	6.0	3.0	6.0	8.25
Responsible_PM	5.50	6.0	3.0	6.0	9.00
Safe_PM	7.40	9.0	6.0	9.0	9.00
CWPM	42.05	45.0	32.0	45.0	52.25

Visualize

In [13]:
```
#visualize univariate plots
uni_vis(all_variables, 'Univariate Plots')
```



Transformation

In [14]:
```
#one hot encoding
df_clean = pd.get_dummies(df, columns = one_hots, drop_first=True)
df_clean
```

Out[14]:

	Respectful_AM	Responsible_AM	Safe_AM	Respectful_PM	Responsible_PM	Safe_PM
0	9	9	9	9	9	9
1	7	7	9	9	9	9
2	4	6	9	9	9	9
3	2	4	9	3	3	5
4	4	4	9	3	3	9
5	6	7	6	3	3	6
6	2	0	9	0	0	0
7	5	5	6	0	0	3
8	4	6	9	6	6	9
9	7	8	9	3	3	6
10	6	4	6	6	6	9
11	4	4	9	0	0	6
12	2	0	9	9	9	9
13	6	6	9	9	9	9
14	7	6	8	6	6	9
15	4	6	9	8	8	9
16	6	6	9	4	5	6
17	2	0	9	8	8	9
18	4	4	9	3	5	8
19	8	7	9	8	9	9

In [15]:
```
df.columns
```

Out[15]:
```
Index(['Check-in_AM', 'Respectful_AM', 'Responsible_AM', 'Safe_AM',
       'Check-in_PM', 'Respectful_PM', 'Responsible_PM', 'Safe_PM', 'CWP
M'],
      dtype='object')
```

In [16]:
```
df_clean.columns
```

Out[16]:
```
Index(['Respectful_AM', 'Responsible_AM', 'Safe_AM', 'Respectful_PM',
       'Responsible_PM', 'Safe_PM', 'CWPM', 'Check-in_AM_Green',
       'Check-in_AM_Red', 'Check-in_AM_Yellow', 'Check-in_PM_Green',
       'Check-in_PM_Red', 'Check-in_PM_Yellow'],
      dtype='object')
```

In [17]:
```
dummies = ['Check-in_AM_Green',
       'Check-in_AM_Red', 'Check-in_AM_Yellow', 'Check-in_PM_Green',
       'Check-in_PM_Red', 'Check-in_PM_Yellow']

to_remove = ['Check-in_AM', 'Check-in_PM']

for variable in dummies:
    predictors.append(variable)

for variable in to_remove:
    predictors.remove(variable)



print(predictors)
```

```
['Respectful_AM', 'Responsible_AM', 'Safe_AM', 'Respectful_PM', 'Responsibl
e_PM', 'Safe_PM', 'Check-in_AM_Green', 'Check-in_AM_Red', 'Check-in_AM_Yell
ow', 'Check-in_PM_Green', 'Check-in_PM_Red', 'Check-in_PM_Yellow']
```

Initial Model

In [26]:
```
X = df_clean[predictors]
X = sm.add_constant(X)
Y = df_clean[target]

model = sm.OLS(Y, X)
result = model.fit()
```

In [27]:
```
result.summary()
```

Out[27]:

OLS Regression Results

Dep. Variable:	CWPM	**R-squared:**	0.920
Model:	OLS	**Adj. R-squared:**	0.783
Method:	Least Squares	**F-statistic:**	6.719
Date:	Sun, 07 Apr 2024	**Prob (F-statistic):**	0.00896
Time:	12:33:39	**Log-Likelihood:**	-61.342
No. Observations:	20	**AIC:**	148.7
Df Residuals:	7	**BIC:**	161.6
Df Model:	12		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	5.0048	45.075	0.111	0.915	-101.581	111.590
Respectful_AM	-1.6997	2.791	-0.609	0.562	-8.300	4.900
Responsible_AM	0.4282	1.575	0.272	0.794	-3.295	4.151
Safe_AM	0.6151	4.065	0.151	0.884	-8.997	10.228
Respectful_PM	0.9223	4.767	0.193	0.852	-10.350	12.195
Responsible_PM	-0.1013	4.855	-0.021	0.984	-11.582	11.379
Safe_PM	1.8307	2.337	0.783	0.459	-3.695	7.357
Check-in_AM_Green	11.4913	10.390	1.106	0.305	-13.077	36.059
Check-in_AM_Red	27.9051	13.598	2.052	0.079	-4.249	60.059
Check-in_AM_Yellow	22.1167	7.637	2.896	0.023	4.057	40.176
Check-in_PM_Green	12.7957	7.594	1.685	0.136	-5.161	30.753
Check-in_PM_Red	-24.9460	18.015	-1.385	0.209	-67.545	17.653
Check-in_PM_Yellow	24.9337	8.627	2.890	0.023	4.533	45.334

Omnibus:	2.313	**Durbin-Watson:**	2.656
Prob(Omnibus):	0.315	**Jarque-Bera (JB):**	1.569
Skew:	0.681	**Prob(JB):**	0.456
Kurtosis:	2.836	**Cond. No.**	387.

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Reduce Model

In [37]:

```
#reduce manually based on t-stat, p-values, and potential multicollinearity
manual_reduce = [
       'Check-in_PM_Yellow', 'Check-in_PM_Green',
        'Check-in_AM_Yellow', 'Safe_PM', 'Respectful_AM'
       ]
X = df_clean[manual_reduce]
#X = sm.add_constant(X)

manual_red_model = sm.OLS(Y, X)
manual_red_result = manual_red_model.fit()
manual_red_result.summary()
```

Out[37]:

OLS Regression Results

Dep. Variable:	CWPM	**R-squared (uncentered):**	0.973
Model:	OLS	**Adj. R-squared (uncentered):**	0.964
Method:	Least Squares	**F-statistic:**	108.4
Date:	Sun, 07 Apr 2024	**Prob (F-statistic):**	3.16e-11
Time:	12:41:56	**Log-Likelihood:**	-68.759
No. Observations:	20	**AIC:**	147.5
Df Residuals:	15	**BIC:**	152.5
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Check-in_PM_Yellow	30.5856	5.464	5.598	0.000	18.940	42.231
Check-in_PM_Green	12.9302	5.378	2.404	0.030	1.466	24.394
Check-in_AM_Yellow	9.9375	4.613	2.154	0.048	0.104	19.771
Safe_PM	3.9126	0.709	5.522	0.000	2.402	5.423
Respectful_AM	-0.3236	0.927	-0.349	0.732	-2.300	1.653

Omnibus:	0.161	**Durbin-Watson:**	2.703
Prob(Omnibus):	0.923	**Jarque-Bera (JB):**	0.034
Skew:	-0.049	**Prob(JB):**	0.983
Kurtosis:	2.825	**Cond. No.**	29.5

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

result = manual_red_result

In [38]:
```
#check for Multicolinearity
X = df_clean[['Check-in_PM_Yellow', 'Check-in_PM_Green',
        'Check-in_AM_Yellow', 'Safe_PM']]
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(X.values, i) for i in range(X
vif["features"] = X.columns
vif
```

Out[38]:

	VIF Factor	features
0	1.495203	Check-in_PM_Yellow
1	2.621424	Check-in_PM_Green
2	2.239277	Check-in_AM_Yellow
3	4.099763	Safe_PM

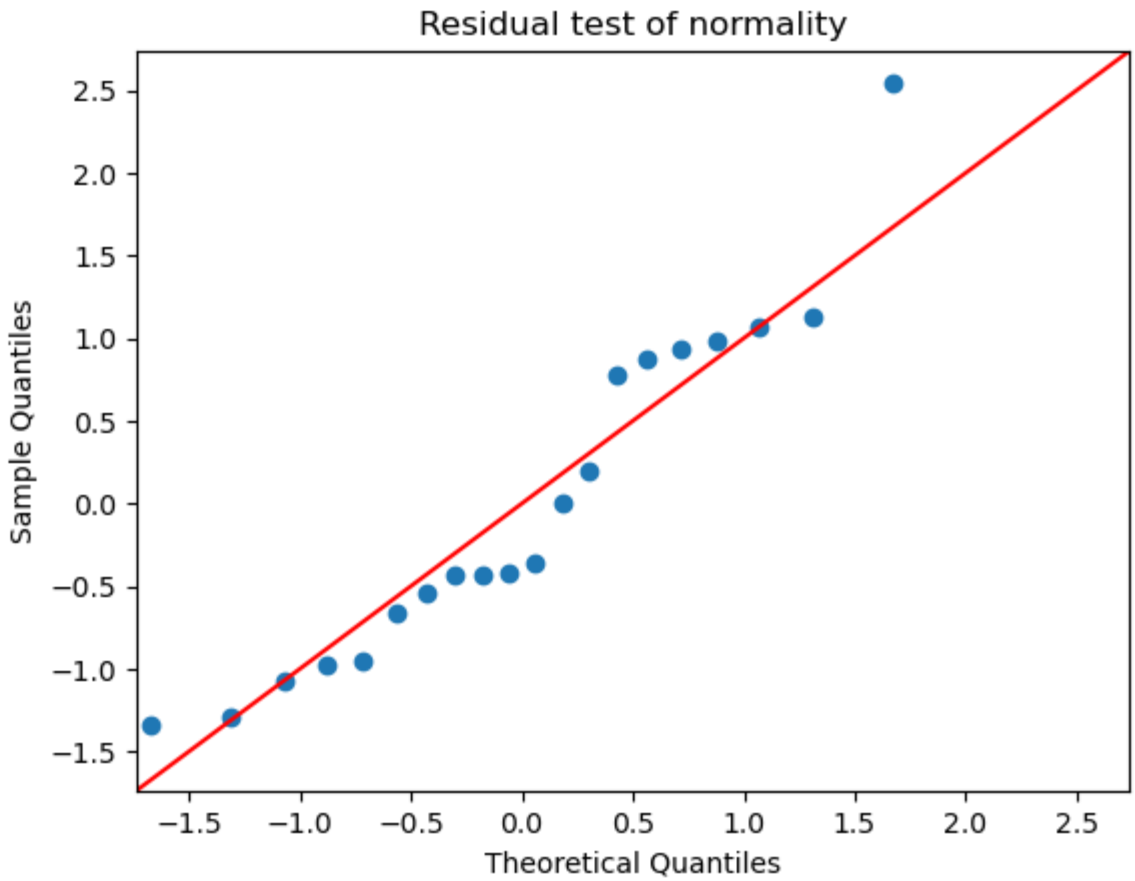
Residual Evaluation

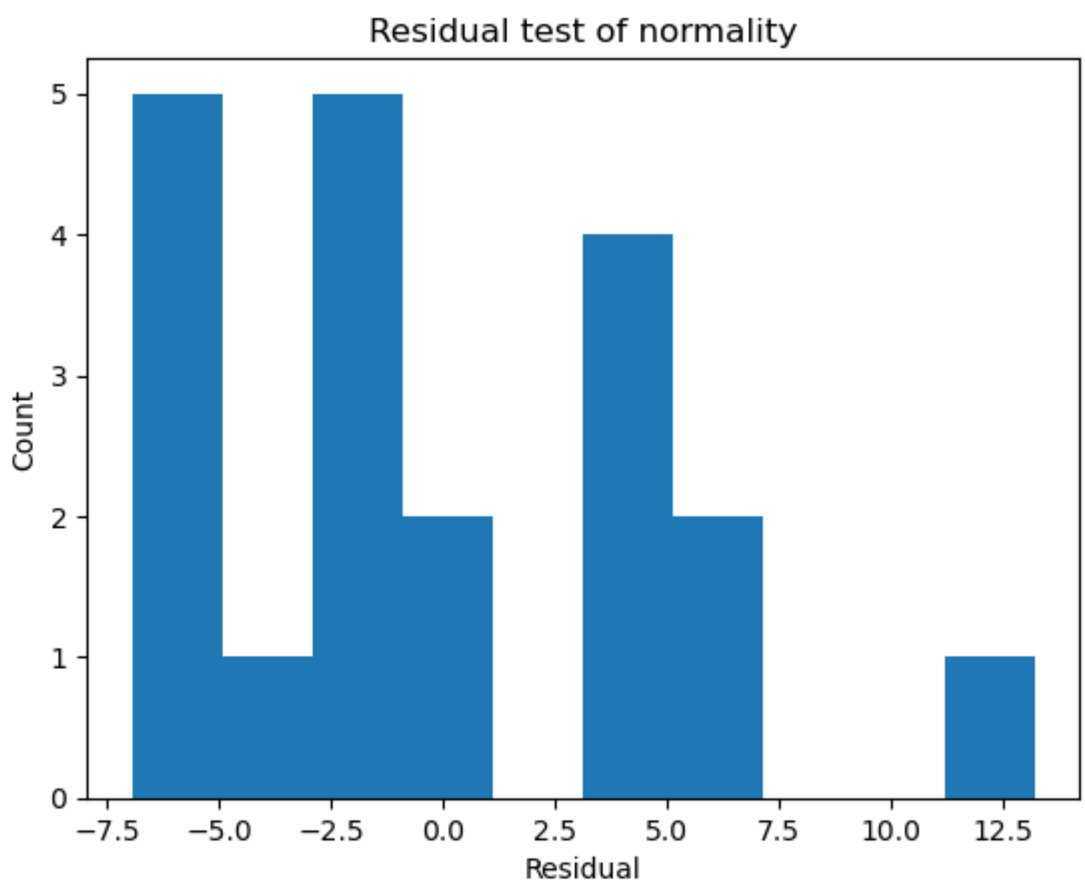
In [39]:
```
#Residual Standard Error
```

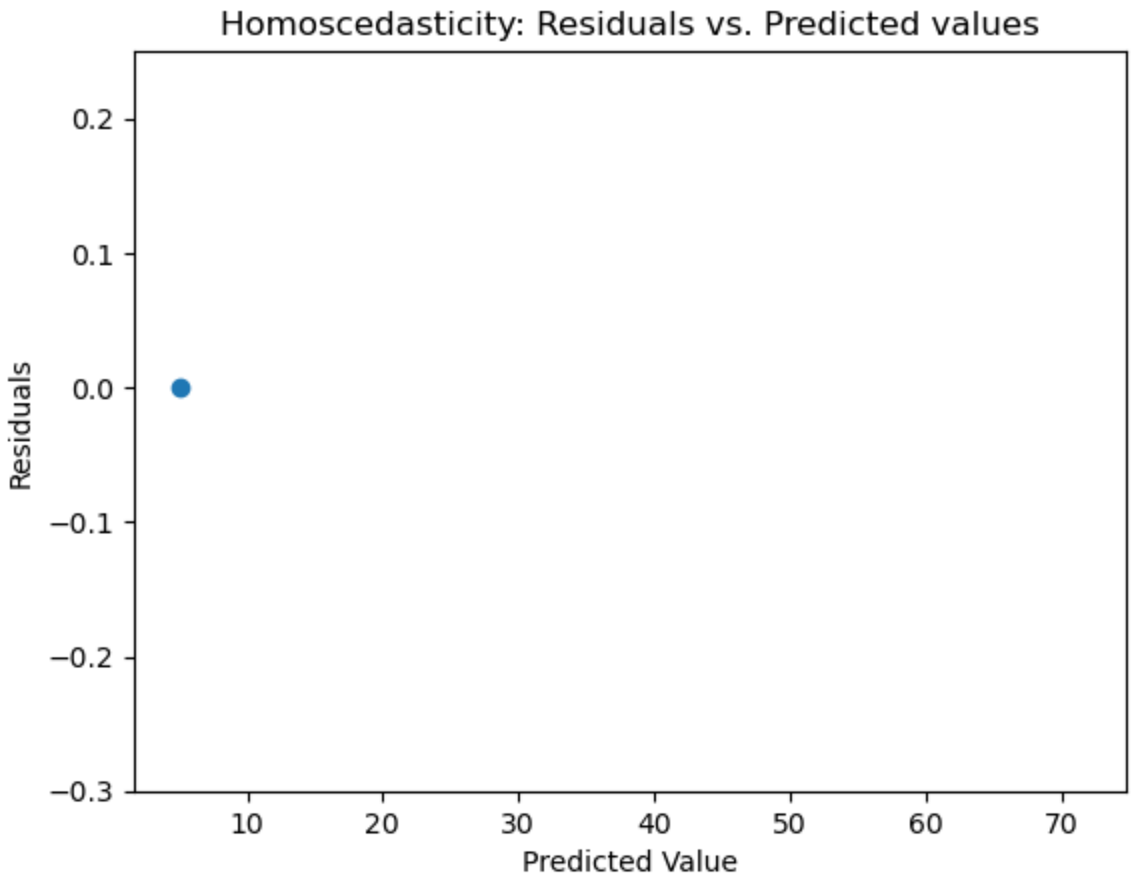
$$RSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n-p-1}}$$

In [41]:
```
#orginal full model
residual_eval(result)
```

```
Residual Standard Error:0.23281184793100002

Adjusted R-square:0.783160913141995
AIC:148.684613827833
```


Residual test of normality
Sample Quantiles
Theoretical Quantiles
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.5 −1.0 −0.5 0.0 0.5 1.0 1.5 2.0 2.5


Residual test of normality
Count
Residual
5
4
3
2
1
0
−7.5 −5.0 −2.5 0.0 2.5 5.0 7.5 10.0 12.5



Reduced based on a stepwise function of eliminating variables based on max p-values until all p-values are less than .05

residual_eval(reduced_model)

```
In [ ]:
```