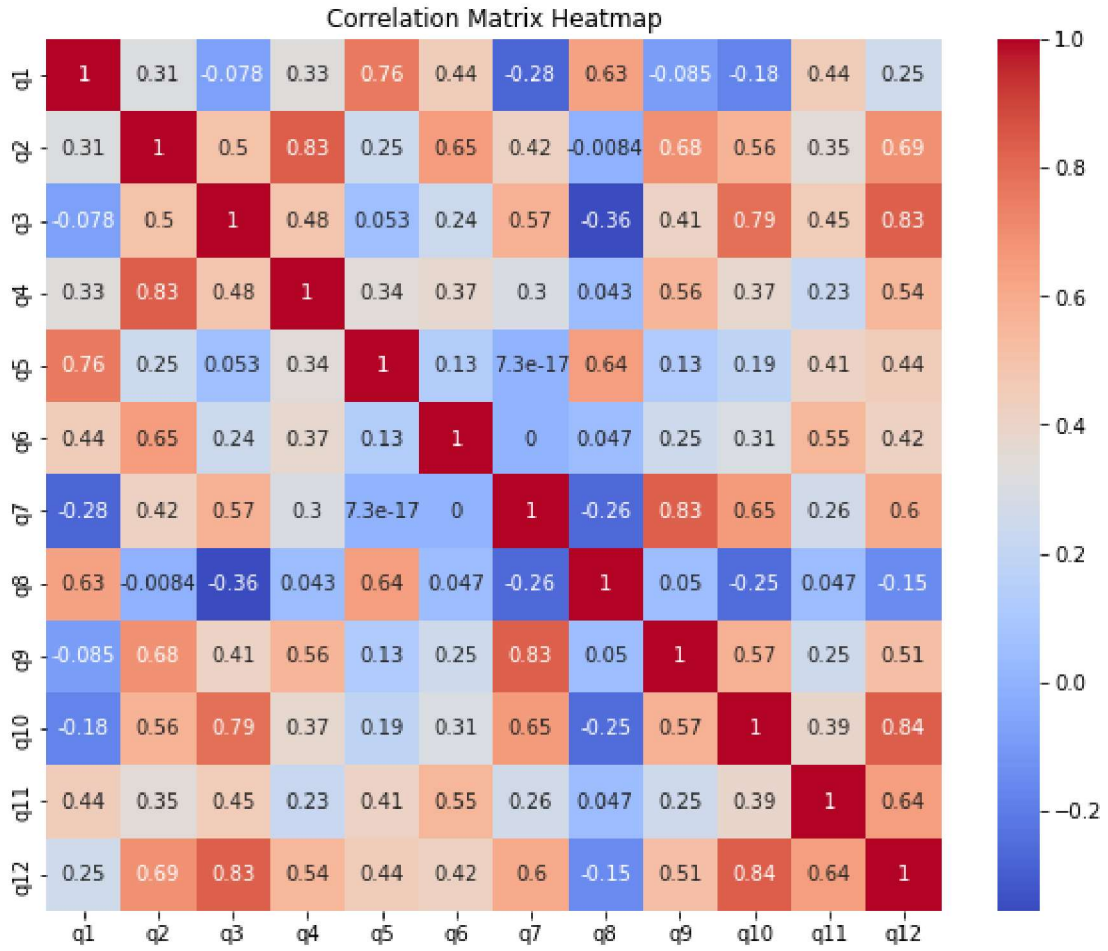
In [28]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import FactorAnalysis
from scipy.stats import pearsonr
from factor_analyzer import FactorAnalyzer
from factor_analyzer.factor_analyzer import calculate_bartlett_sphericity
```

In [29]:
```
data = pd.read_csv('data.csv')
```

In [30]:
```
corr_matrix = data.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', cbar=True)
plt.title('Correlation Matrix Heatmap')
plt.show()
```



In [31]:
```
chi_square_value, p_value = calculate_bartlett_sphericity(data)
kmo_all, kmo_model = calculate_kmo(data)

print("Bartlett's test p-value:", p_value)
print("KMO:", kmo_model)
```

```
Bartlett's test p-value: nan
KMO: 0.4178701574240153

C:\Users\manoj\AppData\Roaming\Python\Python39\site-packages\factor_anal
yzer\factor_analyzer.py:108: RuntimeWarning: invalid value encountered i
n log
  statistic = -np.log(corr_det) * (n - 1 - (2 * p + 5) / 6)
C:\Users\manoj\AppData\Roaming\Python\Python39\site-packages\factor_anal
yzer\utils.py:244: UserWarning: The inverse of the variance-covariance m
atrix was calculated using the Moore-Penrose generalized matrix inversio
n, due to its determinant being at or very close to zero.
  warnings.warn(
```

In [32]:
```
fa = FactorAnalyzer(n_factors=12, rotation=None)
fa.fit(data)
```

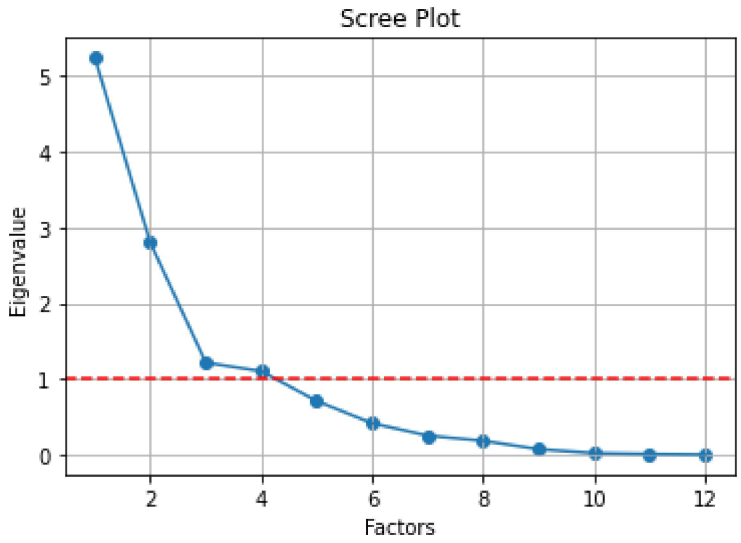
Out[32]:
```
FactorAnalyzer(n_factors=12, rotation=None, rotation_kwargs={})
```

In [33]:
```
ev, v = fa.get_eigenvalues()
total_variance = np.sum(v)
explained_variance = v / total_variance
cumulative_variance = np.cumsum(explained_variance)

explained_variance_table = pd.DataFrame({'Total': ev, '% of variance': exp
print(explained_variance_table)
```

	Total	% of variance	Accumulated %
0	5.243090e+00	43.855405	43.855405
1	2.798730e+00	23.392500	67.247905
2	1.213487e+00	10.119259	77.367164
3	1.100978e+00	9.178906	86.546070
4	7.066555e-01	5.876164	92.422234
5	4.123137e-01	3.412298	95.834532
6	2.489738e-01	2.044956	97.879488
7	1.806400e-01	1.473955	99.353442
8	6.983187e-02	0.547178	99.900621
9	1.765525e-02	0.109825	100.010446
10	7.643564e-03	0.025745	100.036191
11	3.410905e-16	-0.036191	100.000000

In [34]:
```
plt.scatter(range(1, data.shape[1] + 1), ev)
plt.plot(range(1, data.shape[1] + 1), ev)
plt.axhline(y=1, color='r', linestyle='--')
plt.title('Scree Plot')
plt.xlabel('Factors')
plt.ylabel('Eigenvalue')
plt.grid()
plt.show()
```

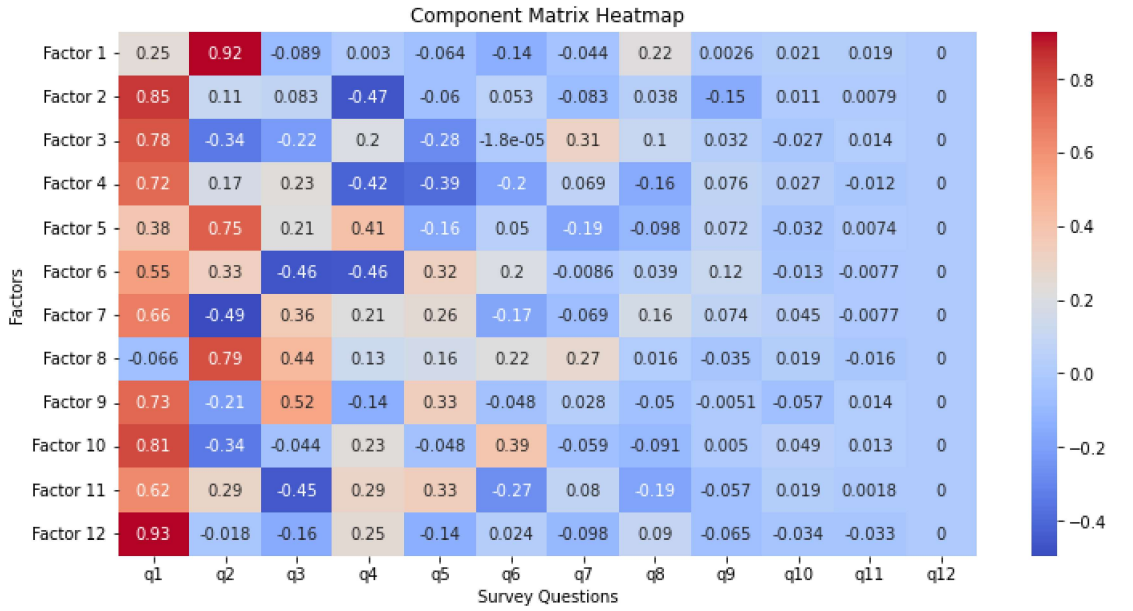


In [35]:
```
communalities = fa.get_communalities()
print('Communalities:', communalities)
```

```
Communalities: [0.99585362 0.99603047 0.99526646 0.99513599 0.99579346
0.99506102
 0.99537278 0.99501659 0.99560153 0.99547889 0.99500924 0.99537996]
```

In [36]:

```
component_matrix = fa.loadings_
plt.figure(figsize=(12, 6))
sns.heatmap(component_matrix, annot=True, cmap='coolwarm', cbar=True, xtic
plt.title('Component Matrix Heatmap')
plt.xlabel('Survey Questions')
plt.ylabel('Factors')
plt.show()
```



In [37]:
```
fa_rotated = FactorAnalyzer(n_factors=4, rotation='varimax') # Use 4 facto
fa_rotated.fit(data)
rotated_component_matrix = fa_rotated.loadings_
print(rotated_component_matrix)
plt.figure(figsize=(12, 6))
sns.heatmap(rotated_component_matrix, annot=True, cmap='coolwarm', cbar=Tr
plt.title('Rotated Component Matrix Heatmap')
plt.xlabel('Survey Questions')
plt.ylabel('Factors')
plt.show()
```

```
[[ 0.05045944  0.82466775 -0.25866884  0.45148674]
 [ 0.26372636  0.06917853  0.4807481   0.84406159]
 [ 0.78271412 -0.18827248  0.27826557  0.2162073 ]
 [ 0.21969012  0.16978379  0.40943895  0.57539038]
 [ 0.27752428  0.91362178  0.07341176  0.05296167]
 [ 0.24454064  0.10600782 -0.06047421  0.71548571]
 [ 0.46649362 -0.15682409  0.75009523 -0.05147179]
 [-0.29015616  0.78142127  0.03426494  0.00847885]
 [ 0.18220743  0.03916914  0.92389319  0.27119161]
 [ 0.73874288 -0.11770063  0.44112452  0.16032462]
 [ 0.57063314  0.27567185 -0.02568901  0.31563736]
 [ 0.89461369  0.15186698  0.29465791  0.32562819]]
```