Алешко Альберт Вариант 1

Задание 3

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
from scipy.stats import pearsonr, spearmanr
import pingouin as pg
import tqdm
from statsmodels.formula.api import ols
plt.style.use('Solarize_Light2') # Функция для задания стиля графикам
```

In [2]:
```
sheet_name = '2-1'
# sheet_name = '1вар-адекв'
data = pd.read_excel('data2.xlsx', sheet_name=sheet_name,
                     header=None, names=['var1', 'var2', 'var3', 'var4', 'var5']) # читаем из файла все выборки
# data# выводим их
```

In [3]:
```
length = len(data.T)
```

In [4]:
```
def get_correlation(df, corr_func):
    names = df.columns
    correlation = np.zeros((length, length))
    correlation[range(length), range(length)] = 1
    p_values = np.zeros((length, length))
    p_values[range(length), range(length)] = 1

    for i in range(len(names)):
        for j in range(i + 1, len(names)):
            res = corr_func(df[names[i]], df[names[j]])
            correlation[i, j] = correlation[j, i] = res[0]
            p_values[i, j] = p_values[j, i] = res[1]
    df_correlation = pd.DataFrame(correlation)
    df_p_values = pd.DataFrame(p_values)
    df_correlation.columns = df_p_values.columns = names
    df_correlation.index = df_p_values.index = names

    return df_correlation, df_p_values
```

In [5]:
```
corr, p_vals = get_correlation(data, pearsonr)
```

In [6]:
```
sns.heatmap(corr, annot=True, vmin=-1, vmax=1);
```

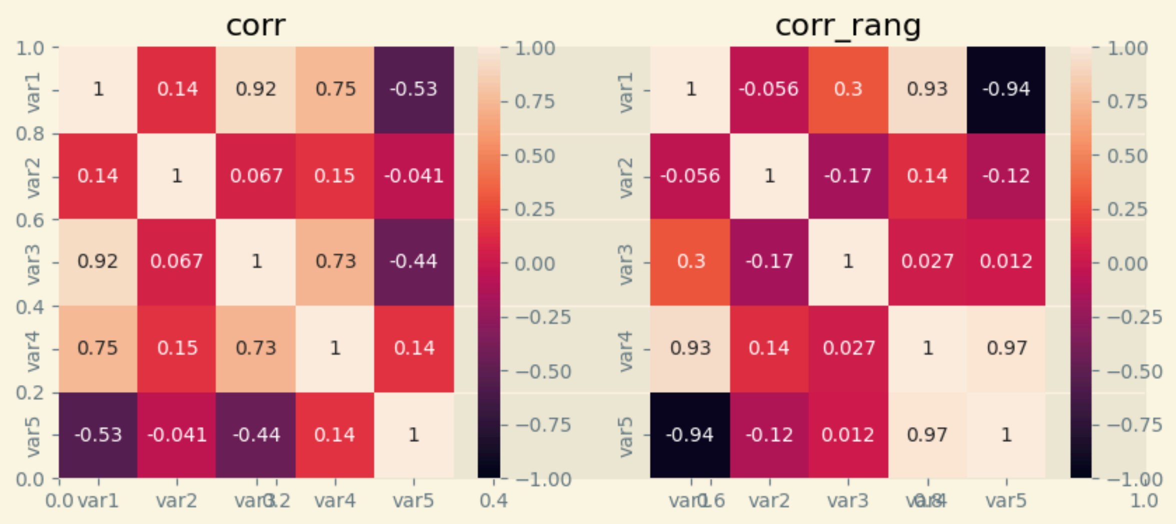
In [7]:
```
sns.heatmap(p_vals, annot=True, vmin=0, vmax=1);
```

In [8]:
```
def get_part_corr(df):
    names = df.columns
    correlation = np.zeros((length, length))
    correlation[range(length), range(length)] = 1
    p_values = np.zeros((length, length))
    p_values[range(length), range(length)] = 1

    for i in range(len(names)):
        for j in range(i+1, len(names)):
            co_names = list(df.columns)
            co_names.remove(names[i])
            if names[j] in co_names:
                co_names.remove(names[j])
            # print((names[i],names[j]),co_names)
            res = pg.partial_corr(data=df, x=names[i], y=names[j], covar=co_names)
            correlation[i, j] = correlation[j, i] = res['r'].iloc[0]
            p_values[i, j] = p_values[j, i] = res['p-val'].iloc[0]
    df_correlation = pd.DataFrame(correlation)
    df_p_values = pd.DataFrame(p_values)
    df_correlation.columns = df_p_values.columns = names
```

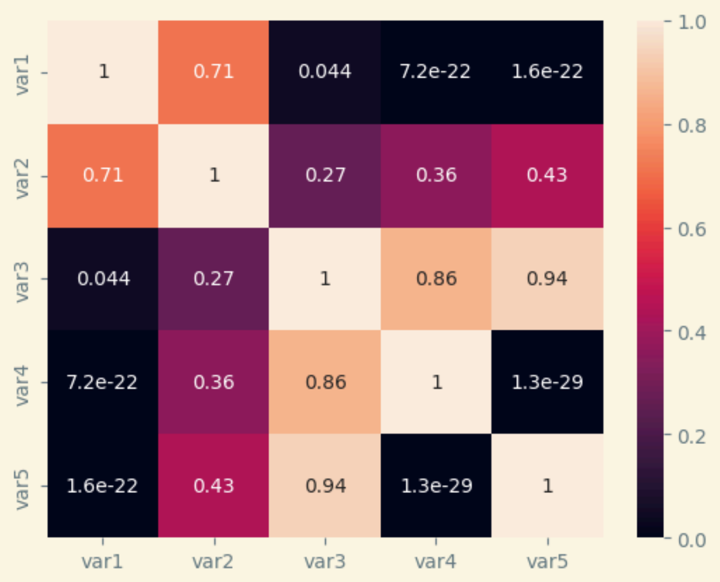
```
    df_correlation.index = df_p_values.index = names

    return df_correlation, df_p_values
```

In [9]:
```
# partial_corr = pg.partial_corr(data=data, x='1', y='2', covar=['3','4','5'])
corr_part, p_vals = get_part_corr(data)
# print(partial_corr)
```

In [10]:
```
fig = plt.subplots(figsize=(10, 4))

plt.subplot(121)
plt.title('corr')
sns.heatmap(corr, annot=True, vmin=-1, vmax=1);

plt.subplot(122)
plt.title('corr_rang')
sns.heatmap(corr_part, annot=True, vmin=-1, vmax=1);
```



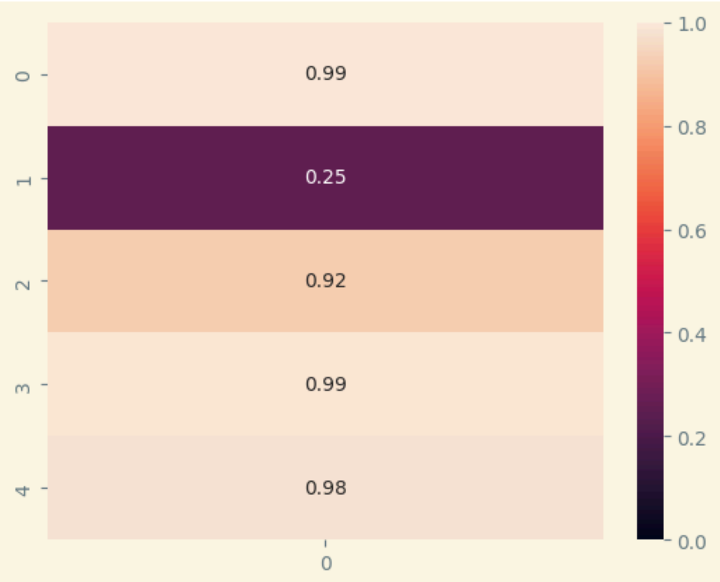
In [11]:
```
sns.heatmap(p_vals, annot=True, vmin=0, vmax=1);
```



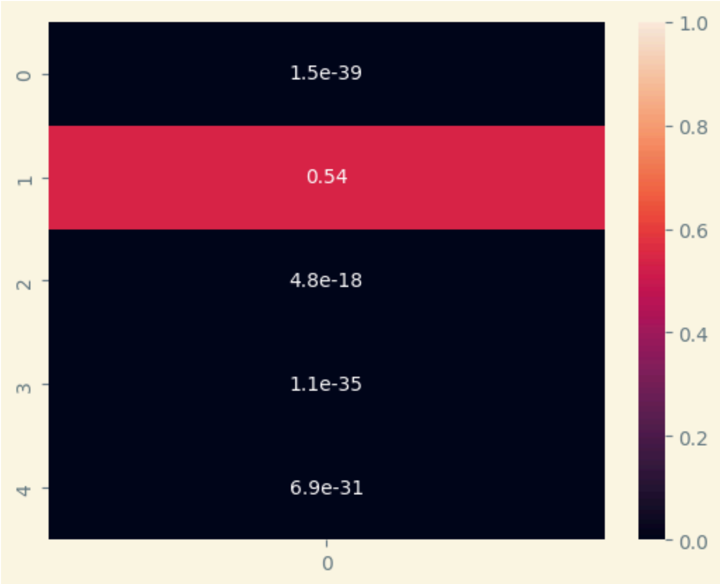
In [12]:
```
def multiple_correlation(df):
    names = df.columns
    length = len(names)
    correlation = np.zeros((length))
    p_values = np.zeros((length))

    for i, name in enumerate(names):
        formula = name + ' ~ ' + ' + '.join([n for j, n in enumerate(names) if j != i])
        mod = ols(formula=formula, data=df)
        res = mod.fit()
        correlation[i] = res.rsquared ** 0.5
        p_values[i] = res.f_pvalue

    return correlation, p_values
```

In [13]:
```
multi_corr, p_vals = multiple_correlation(data)
```

In [14]:
```
sns.heatmap(multi_corr[..., None], annot=True, vmin=0, vmax=1);
```

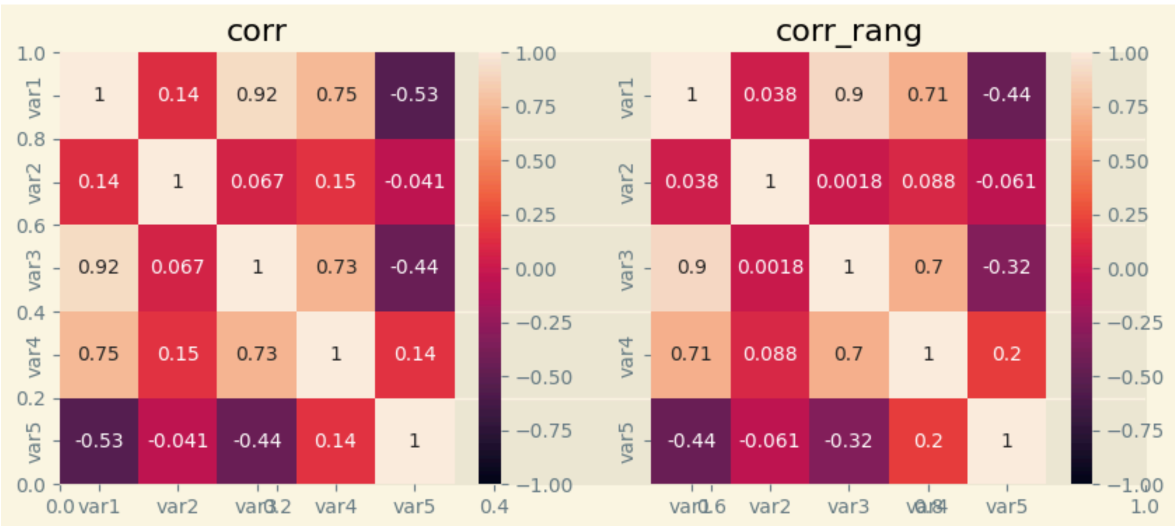


In [15]:
```
sns.heatmap(p_vals[..., None], annot=True, vmin=0, vmax=1);
```

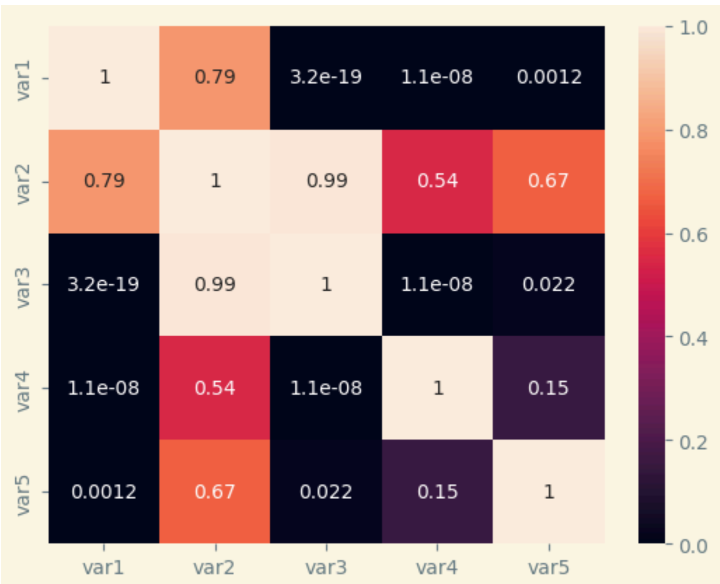


In [16]:
```
corr_rang, p_vals = get_correlation(data, spearmanr)
```

In [17]:
```
fig = plt.subplots(figsize=(10, 4))

plt.subplot(121)
sns.heatmap(corr, annot=True, vmin=-1, vmax=1);
plt.title('corr')

plt.subplot(122)
plt.title('corr_rang')
sns.heatmap(corr_rang, annot=True, vmin=-1, vmax=1);
```



In [18]:
```
sns.heatmap(p_vals, annot=True, vmin=0, vmax=1);
```



In [19]:
```
from math import *
import scipy as sci
```

In [20]:
```
def Cheddock_scale_check(r, name='r'):
    # задаем шкалу Чеддока
        # no correlation (n <= 0.1)'
        # very weak (0.1 < n <= 0.2)'
        # weak (0.2 < n <= 0.3)'
        # moderate (0.3 < n <= 0.5)'
        # perceptible (0.5 < n <= 0.7)'
        # high (0.7 < n <= 0.9)'
        # very high (0.9 < n <= 0.99)'
        # functional (n > 0.99)'
    Cheddock_scale = {
        f'no correlation':    0.1,
        f'very weak':   0.2,
        f'weak ':        0.3,
        f'moderate':    0.5,
        f'perceptible': 0.7,
        f'high':        0.9,
        f'very high':  0.99,
        f'functional':        1.0}

    r_scale = list(Cheddock_scale.values())
    for i, elem in enumerate(r_scale):
        if abs(r) <= elem:
            conclusion_Cheddock_scale = list(Cheddock_scale.keys())[i]
            break
    return conclusion_Cheddock_scale
```

In [21]:
```
def corr_ratio_check(X, Y, p_level=0.95, orientation='XY', scale='Cheddok'):
    a_level = 1 - p_level
    name = f'{X.name} {Y.name}'
    X = np.array(X)
    Y = np.array(Y)
    n_X = len(X)
```

```python
    n_Y = len(Y)
    # запишем данные в DataFrame
    matrix_XY_df = pd.DataFrame({
        'X': X,
        'Y': Y})
    # число интервалов группировки
    group_int_number = lambda n: round (3.31*log(n_X, 10)+1) if round (3.31*log(n_X, 10)+1) >=2 else 2
    K_X = group_int_number(n_X)
    K_Y = group_int_number(n_Y)
    # группировка данных и формирование корреляционной таблицы
    cut_X = pd.cut(X, bins=K_X)
    cut_Y = pd.cut(Y, bins=K_Y)
    matrix_XY_df['cut_X'] = cut_X
    matrix_XY_df['cut_Y'] = cut_Y
    CorrTable_df = pd.crosstab(
        index=matrix_XY_df['cut_X'],
        columns=matrix_XY_df['cut_Y'],
        rownames=['cut_X'],
        colnames=['cut_Y'])
    CorrTable_np = np.array(CorrTable_df)
    K_X = len(CorrTable_np)
    K_Y = len(CorrTable_np[0])
    # итоги корреляционной таблицы по строкам и столбцам
    n_group_X = [np.sum(CorrTable_np[i]) for i in range(K_X)]
    n_group_Y = [np.sum(CorrTable_np[:,j]) for j in range(len(CorrTable_np[0]))]
    # среднегрупповые значения переменной X
    Xboun_mean = [(CorrTable_df.index[i].left + CorrTable_df.index[i].right)/2 for i in range(K_X)]
    Xboun_mean[0] = (np.min(X) + CorrTable_df.index[0].right)/2    # исправляем значения в крайних интервалах
    Xboun_mean[K_X-1] = (CorrTable_df.index[K_X-1].left + np.max(X))/2
    # среднегрупповые значения переменной Y
    Yboun_mean = [(CorrTable_df.columns[j].left + CorrTable_df.columns[j].right)/2 for j in range(K_Y)]
    Yboun_mean[0] = (np.min(Y) + CorrTable_df.columns[0].right)/2    # исправляем значения в крайних интервалах
    Yboun_mean[K_Y-1] = (CorrTable_df.columns[K_Y-1].left + np.max(Y))/2
    # средневзвешенные значения X и Y для каждой группы
    Xmean_group = [np.sum(CorrTable_np[:,j] * Xboun_mean) / n_group_Y[j] for j in range(K_Y)]
    Ymean_group = [np.sum(CorrTable_np[i] * Yboun_mean) / n_group_X[i] for i in range(K_X)]
    # общая дисперсия X и Y
    Sum2_total_X = np.sum(n_group_X * (Xboun_mean - np.mean(X))**2)
    Sum2_total_Y = np.sum(n_group_Y * (Yboun_mean - np.mean(Y))**2)
    # межгрупповая дисперсия X и Y (дисперсия групповых средних)
    Sum2_between_group_X = np.sum(n_group_Y * (Xmean_group - np.mean(X))**2)
    Sum2_between_group_Y = np.sum(n_group_X * (Ymean_group - np.mean(Y))**2)
    # эмпирическое корреляционное отношение
    corr_ratio_XY = sqrt(Sum2_between_group_Y / Sum2_total_Y)
    corr_ratio_YX = sqrt(Sum2_between_group_X / Sum2_total_X)
    try:
        if orientation!='XY' and orientation!='YX':
            raise ValueError("Error! Incorrect orientation!")
        if orientation=='XY':
            corr_ratio = corr_ratio_XY
        elif orientation=='YX':
            corr_ratio = corr_ratio_YX
    except ValueError as err:
        print(err)
    # проверка гипотезы о значимости корреляционного отношения
    F_corr_ratio_calc = (n_X - K_X)/(K_X - 1) * corr_ratio**2 / (1 - corr_ratio**2)
    dfn = K_X - 1
    dfd = n_X - K_X
    F_corr_ratio_table = sci.stats.f.ppf(p_level, dfn, dfd, loc=0, scale=1)
    a_corr_ratio_calc = 1 - sci.stats.f.cdf(F_corr_ratio_calc, dfn, dfd, loc=0, scale=1)
    conclusion_corr_ratio_sign = 'significance' if F_corr_ratio_calc >= F_corr_ratio_table else 'not significance'
    # доверительный интервал корреляционного отношения
    if F_corr_ratio_calc >= F_corr_ratio_table:
        f1 = round ((K_X - 1 + n_X * corr_ratio**2)**2 / (K_X - 1 + 2 * n_X * corr_ratio**2))
        f2 = n_X - K_X
        z1 = (n_X - K_X) / n_X * corr_ratio**2 / (1 - corr_ratio**2) * 1/sci.stats.f.ppf(p_level, f1, f2, loc=0, scale=1) - (K_X - 1)/n_X
        z2 = (n_X - K_X) / n_X * corr_ratio**2 / (1 - corr_ratio**2) * 1/sci.stats.f.ppf(1 - p_level, f1, f2, loc=0, scale=1) - (K_X - 1)/n_X
        corr_ratio_conf_int_low = sqrt(z1) if sqrt(z1) >= 0 else 0
        corr_ratio_conf_int_high = sqrt(z2) if sqrt(z2) <= 1 else 1
    else:
        corr_ratio_conf_int_low = corr_ratio_conf_int_high = '-'
    # оценка тесноты связи
    if scale=='Cheddok':
        conclusion_corr_ratio_scale = scale + ': ' + Cheddock_scale_check(corr_ratio, name=chr(951))
    elif scale=='Evans':
        conclusion_corr_ratio_scale = scale + ': ' + Evans_scale_check(corr_ratio, name=chr(951))
    # формируем результат
    result = pd.DataFrame({
        'notation': (chr(951)),
        'coef_value': (corr_ratio),
        'c_v_squared': (corr_ratio**2),
        'p_level': (p_level),
        'a_level': (a_level),
        'F_calc': (F_corr_ratio_calc),
        'F_table': (F_corr_ratio_table),
        'F_calc >= F_table': (F_corr_ratio_calc >= F_corr_ratio_table),
        'a_calc': (a_corr_ratio_calc),
        'a_calc <= a_level': (a_corr_ratio_calc <= a_level),
        'significance': (conclusion_corr_ratio_sign),
        'conf_int_low': (corr_ratio_conf_int_low),
        'conf_int_high': (corr_ratio_conf_int_high),
        'scale': (conclusion_corr_ratio_scale)
        },
        index=[name])

    return result
```

In [22]:
```python
names = data.columns
new_df = pd.DataFrame({
        'notation': (),
        'coef_value': (),
        'c_v_squared': (),
        'p_level': (),
        'a_level': (),
        'F_calc': (),
        'F_table': (),
        'F_calc >= F_table': (),
        'a_calc': (),
        'a_calc <= a_level': (),
        'significance': (),
        'conf_int_low': (),
        'conf_int_high': (),
        'scale': ()
        })
for one in names:
    for two in names:
        if(one!=two):
            try:
                res = corr_ratio_check(data[one], data[two])
                new_df = pd.concat([new_df, res])
            except:
                print('error')
```

In [23]:
```python
new_df
```

Out[23]:

	notation	coef_value	c_v_squared	p_level	a_level	F_calc	F_table	F_calc >= F_table	a_calc	a_calc <= a_level	significance	conf_int_low	conf_int_high	scale
var1 var2	η	0.406018	0.164851	0.95	0.05	1.414632	2.318498	0.0	2.311710e-01	0.0	not significance	-	-	Cheddok: moderate
var1 var3	η	0.920520	0.847357	0.95	0.05	39.783996	2.318498	True	5.551115e-16	True	significance	1.612586	1	Cheddok: very high
var1 var4	η	0.702272	0.493185	0.95	0.05	6.973938	2.318498	True	3.177223e-05	True	significance	0.57308	1	Cheddok: high
var1 var5	η	0.618713	0.382805	0.95	0.05	4.445013	2.318498	True	1.393598e-03	True	significance	0.395595	1	Cheddok: perceptible
var2 var1	η	0.404477	0.163602	0.95	0.05	1.401822	2.318498	False	2.360105e-01	False	not significance	-	-	Cheddok: moderate
var2 var3	η	0.476072	0.226645	0.95	0.05	2.100309	2.318498	False	7.286889e-02	False	not significance	-	-	Cheddok: moderate
var2 var4	η	0.481702	0.232037	0.95	0.05	2.165375	2.318498	False	6.513877e-02	False	not significance	-	-	Cheddok: moderate
var2 var5	η	0.272468	0.074239	0.95	0.05	0.574711	2.318498	False	7.482250e-01	False	not significance	-	-	Cheddok: weak
var3 var1	η	0.909746	0.827638	0.95	0.05	34.412455	2.318498	True	7.105427e-15	True	significance	1.490374	1	Cheddok: very high
var3 var2	η	0.336767	0.113412	0.95	0.05	0.916756	2.318498	False	4.922925e-01	False	not significance	-	-	Cheddok: moderate
var3 var4	η	0.756170	0.571794	0.95	0.05	9.569807	2.318498	True	1.111974e-06	True	significance	0.711491	1	Cheddok: high
var3 var5	η	0.468123	0.219139	0.95	0.05	2.011242	2.318498	False	8.492764e-02	False	not significance	-	-	Cheddok: moderate
var4 var1	η	0.695733	0.484045	0.95	0.05	8.255744	2.427040	True	1.447203e-05	True	significance	0.582481	1	Cheddok: perceptible
var4 var2	η	0.320314	0.102601	0.95	0.05	1.006118	2.427040	False	4.254677e-01	False	not significance	-	-	Cheddok: moderate
var4 var3	η	0.736718	0.542754	0.95	0.05	10.445655	2.427040	True	1.187842e-06	True	significance	0.67928	1	Cheddok: high
var4 var5	η	0.266963	0.071269	0.95	0.05	0.675296	2.427040	False	6.443645e-01	False	not significance	-	-	Cheddok: weak
var5 var1	η	0.592440	0.350985	0.95	0.05	3.875701	2.318498	True	3.525059e-03	True	significance	0.343286	0.981747	Cheddok: perceptible
var5 var2	η	0.329227	0.108391	0.95	0.05	0.871233	2.318498	False	5.238241e-01	False	not significance	-	-	Cheddok: moderate
var5 var3	η	0.492239	0.242300	0.95	0.05	2.291777	2.318498	False	5.236408e-02	False	not significance	-	-	Cheddok: moderate
var5 var4	η	0.354154	0.125425	0.95	0.05	1.027787	2.318498	False	4.205297e-01	False	not significance	-	-	Cheddok: moderate