📊 Canonical Correlation Analysis (CCA)

- Canonical Correlation Analysis (CCA) is an advanced statistical technique used to probe the relationships between **two sets of multivariate variables** on the **same subjects.**
- It is particularly applicable in circumstances **where multiple regression would be appropriate**, but there are multiple intercorrelated outcome variables.
- CCA identifies and quantifies the associations among these two variable groups.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Read the dataset

In [3]:
```
mm = pd.read_stata('mmreg.dta')
mm
```

Out[3]:

	id	locus_of_control	self_concept	motivation	read	write	math	s
0	303.0	-0.84	-0.24	1.00	54.799999	64.500000	44.500000	52.
1	404.0	-0.38	-0.47	0.67	62.700001	43.700001	44.700001	52.
2	225.0	0.89	0.59	0.67	60.599998	56.700001	70.500000	58.
3	553.0	0.71	0.28	0.67	62.700001	56.700001	54.700001	58.
4	433.0	-0.64	0.03	1.00	41.599998	46.299999	38.400002	36.
...	...	...	...	...	...	...	...	
595	464.0	0.94	-0.30	1.00	60.099998	67.099998	52.400002	55.
596	291.0	0.23	0.03	1.00	65.400002	56.700001	65.400002	58.
597	348.0	0.46	0.03	1.00	65.400002	51.500000	61.400002	60.
598	193.0	0.51	0.03	1.00	54.799999	54.099998	66.400002	41.
599	380.0	0.25	0.03	0.67	49.500000	51.500000	55.500000	44.

600 rows × 9 columns

In [4]:
```
mm.isna().sum()
```

Out[4]:

	0
id	0
locus_of_control	0
self_concept	0
motivation	0
read	0
write	0
math	0
science	0
female	0

dtype: int64

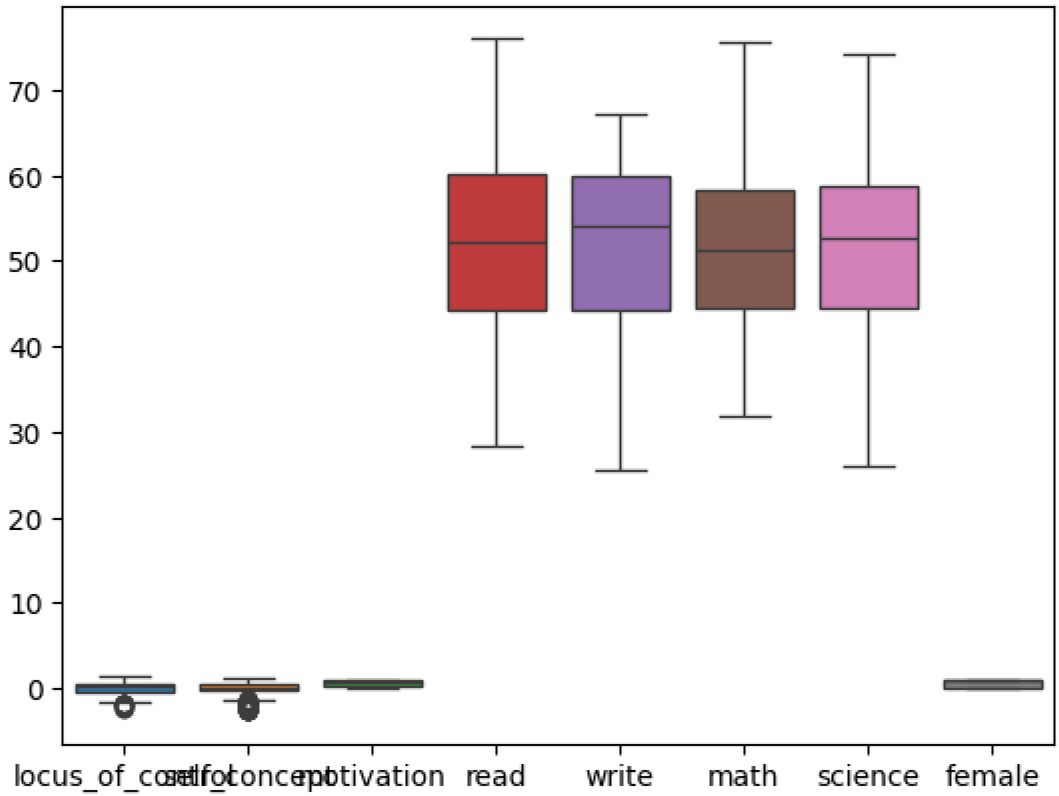
In [5]:
```
mm.describe().T
```

Out[5]:

	count	mean	std	min	25%	50%	7
id	600.0	300.500000	173.348816	1.000000	150.750000	300.500000	450.250
locus_of_control	600.0	0.096533	0.670280	-2.230000	-0.372500	0.210000	0.510
self_concept	600.0	0.004917	0.705512	-2.620000	-0.300000	0.030000	0.440
motivation	600.0	0.660833	0.342729	0.000000	0.330000	0.670000	1.000
read	600.0	51.901833	10.102986	28.299999	44.200001	52.099998	60.099
write	600.0	52.384834	9.726455	25.500000	44.299999	54.099998	59.900
math	600.0	51.848999	9.414738	31.799999	44.500000	51.299999	58.374
science	600.0	51.763332	9.706173	26.000000	44.400002	52.599998	58.650
female	600.0	0.545000	0.498387	0.000000	0.000000	1.000000	1.000

🧑‍💻 Data Preprocessing

In [6]:
```
sns.boxplot(data=mm.drop('id', axis=1))
plt.show()
```



In [7]:

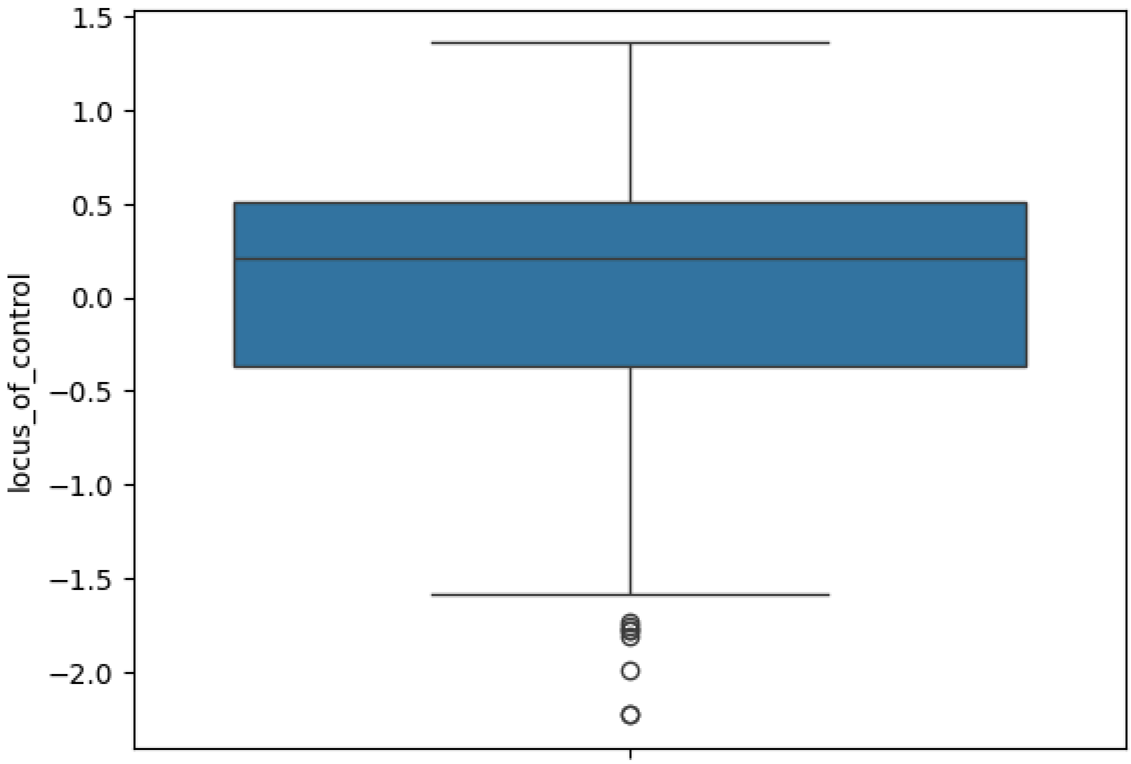
```
# Function to detect outliers using IQR
def detect_outliers_iqr(mm, column):
    q1 = mm[column].quantile(0.25)
    q3 = mm[column].quantile(0.75)
    iqr = q3 - q1
    lower_bound = q1 - 1.5 * iqr
    upper_bound = q3 + 1.5 * iqr
    outliers = mm[(mm[column] < lower_bound) | (mm[column] > upper_bound)]
    return outliers
# Detect outliers in numerical columns
numerical_cols = ['locus_of_control', 'self_concept', 'motivation', 'read', 'write'
for col in numerical_cols:
    outliers = detect_outliers_iqr(mm, col)
    if not outliers.empty:
        print(f"Outliers in '{col}':")

    else:
        print(f"No outliers found in '{col}'")
```

```
Outliers in 'locus_of_control':
Outliers in 'self_concept':
No outliers found in 'motivation'
No outliers found in 'read'
No outliers found in 'write'
No outliers found in 'math'
No outliers found in 'science'
```

In [8]:

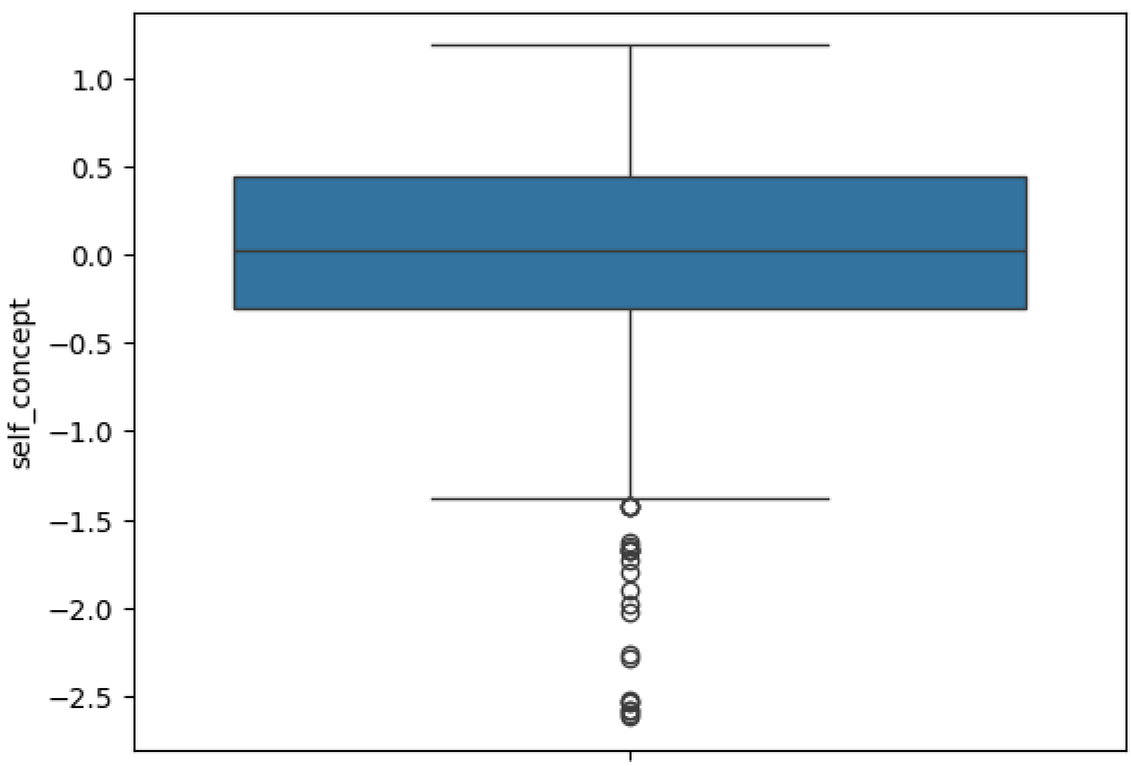
```
sns.boxplot(mm['locus_of_control'])
```

Out[8]: <Axes: ylabel='locus_of_control'>



In [10]:
```
sns.boxplot(mm['self_concept'])
```

Out[10]: <Axes: ylabel='self_concept'>



In this `locus_of_control` & `self_concept` have outliers. So, we need to remove this outliers.

In [11]:
```
df = mm.copy()
```

In [12]:
```
# Step 1: Calculate Q1 (25th percentile) and Q3 (75th percentile)
Q1 = df['locus_of_control'].quantile(0.25)
Q3 = df['locus_of_control'].quantile(0.75)

# Step 2: Calculate IQR
IQR = Q3 - Q1

# Step 3: Define lower and upper bounds
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
```

In [13]:
```
#  Remove the outliers and make a new dataframe
df_no_outliers = df[(df['locus_of_control'] >= lower_bound) & (df['locus_of_control
```

In [14]:
```
df_no_outliers = df[(df['self_concept'] >= lower_bound) & (df['self_concept'] <= up
```

In [15]:
```
new_df = df_no_outliers.copy()
```

In [17]:
```
new_df
```

Out[17]:

	id	locus_of_control	self_concept	motivation	read	write	math	s
0	303.0	-0.84	-0.24	1.00	54.799999	64.500000	44.500000	52.
1	404.0	-0.38	-0.47	0.67	62.700001	43.700001	44.700001	52.
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4	433.0	-0.64	0.03	1.00	41.599998	46.299999	38.400002	36.
...	...	...	...	...	...	...	...	
595	464.0	0.94	-0.30	1.00	60.099998	67.099998	52.400002	55.
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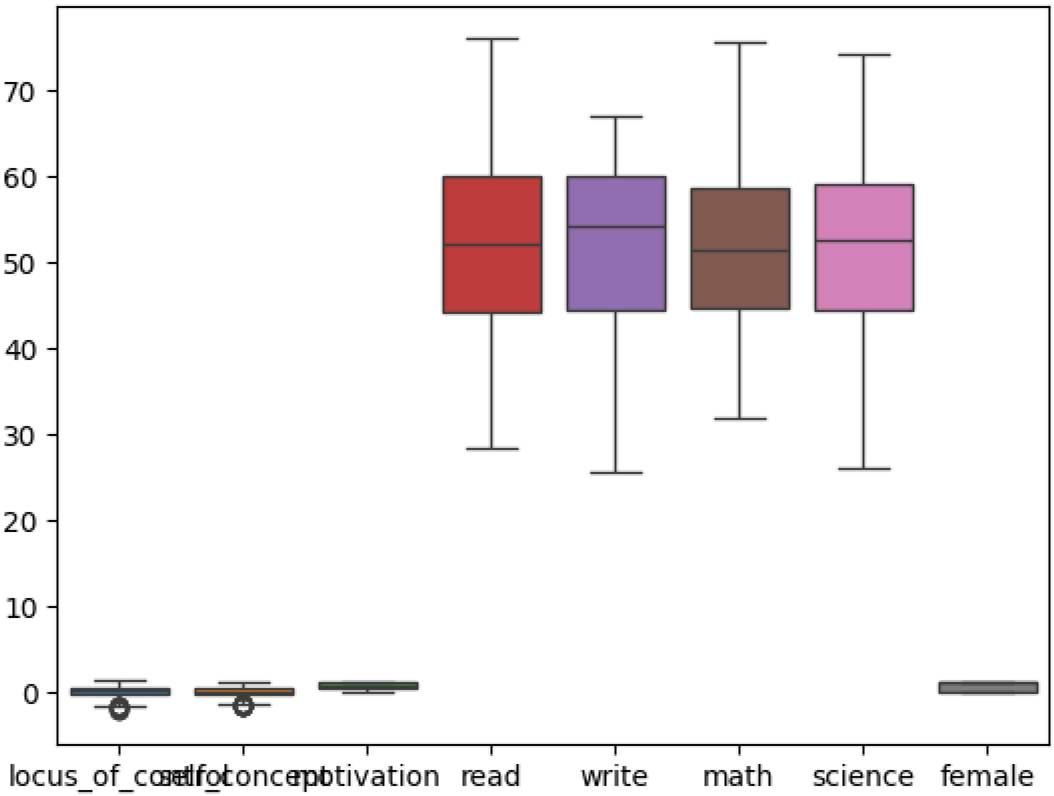
597	348.0	0.46	0.03	1.00	65.400002	51.500000	61.400002	60.
598	193.0	0.51	0.03	1.00	54.799999	54.099998	66.400002	41.
599	380.0	0.25	0.03	0.67	49.500000	51.500000	55.500000	44.

586 rows × 9 columns

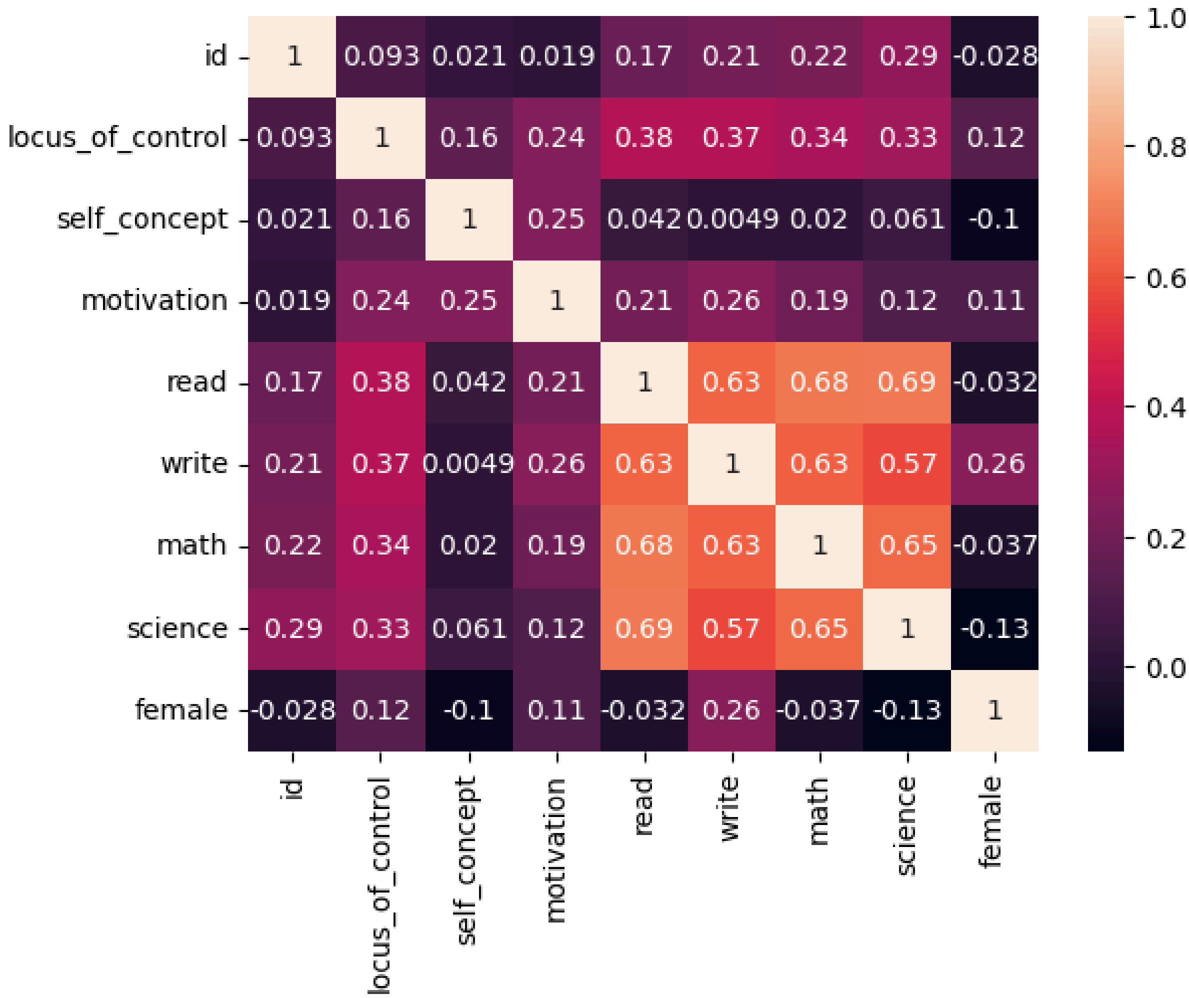
🧑‍💻 After remove outliers here we have 586 rows, that means 14 rows are removed that have outliers.

In [18]:
```
sns.boxplot(data=new_df.drop('id', axis=1))
plt.show()
```



In [19]:
```
sns.heatmap(new_df.corr(), annot=True)
```

Out[19]: <Axes: >



👩‍💻 **Apply Canonical Correlation method**

👩‍💻 **Separate the two variable groups** considering one of "Psychological variables" and another is "Academic variables"

In [20]:
```
# Psychological variables
X = new_df[['locus_of_control', 'self_concept', 'motivation']]

# Academic variables
Y = new_df[['read', 'write', 'math', 'science']]
```

Apply the Canonical Correlation method

In [21]:
```
from sklearn.cross_decomposition import CCA
```

In [31]:
```
cca = CCA(n_components=1)
cca.fit(X, Y)
```

Out[31]:

```
▾ CCA
CCA(n_components=1)
```

In [32]:

```
# Transform the data to get the canonical variates (scores)
X_c, Y_c = cca.transform(X, Y)
```

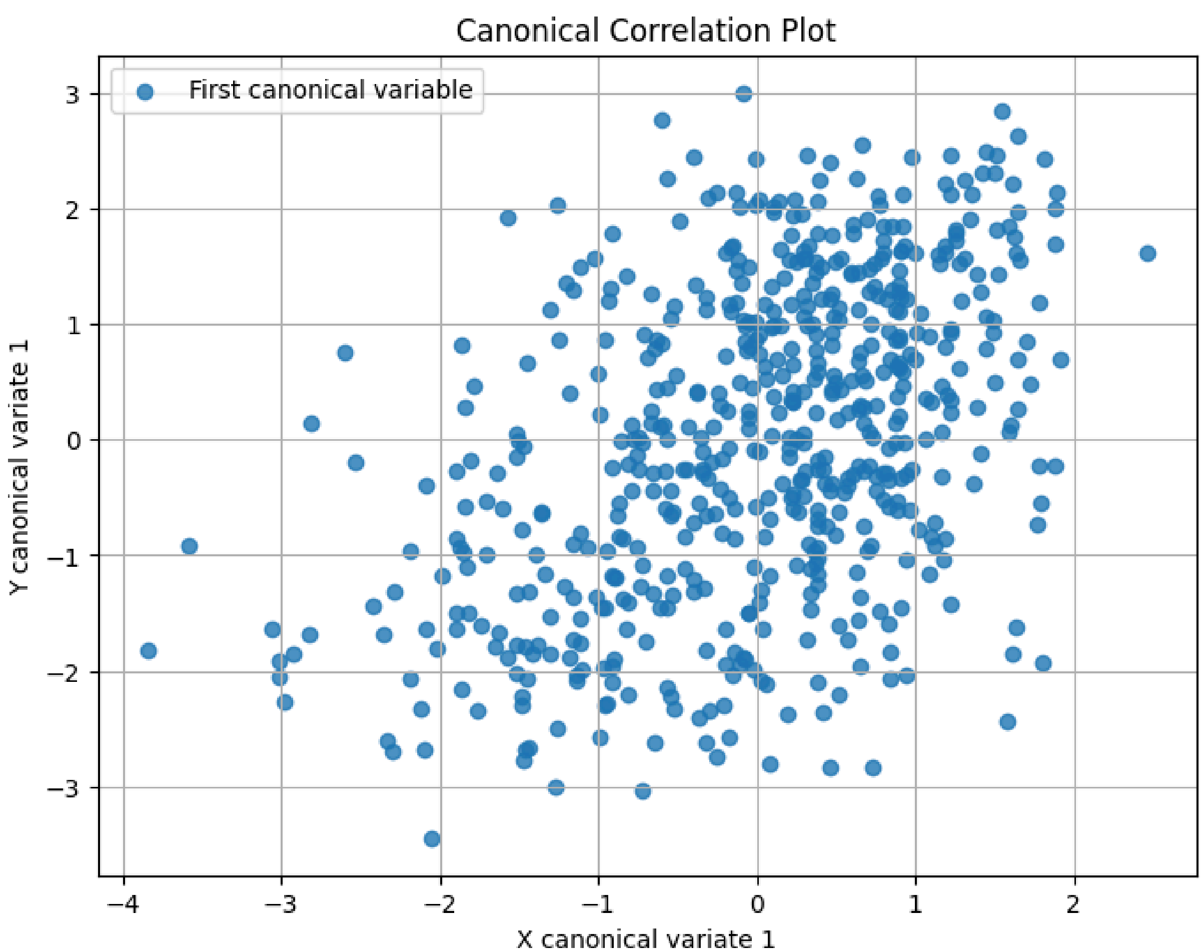
In [33]:

```
# Get the canonical correlation by correlating the transformed data
canonical_correlation = np.corrcoef(X_c[:, 0], Y_c[:, 0])[0, 1]

print(f"Canonical Correlation: {canonical_correlation:.4f}")
```

```
Canonical Correlation: 0.4588
```

In [34]:

```
#Plot the Canonical Variates

plt.figure(figsize=(8, 6))
plt.scatter(X_c[:, 0], Y_c[:, 0], label="First canonical variable", alpha=0.8)
plt.xlabel("X canonical variate 1")
plt.ylabel("Y canonical variate 1")
plt.title("Canonical Correlation Plot")
plt.legend()
plt.grid(True)
plt.show()
```



In [35]:
```
# These show how much each original variable contributes to the canonical variate
X_weights = cca.x_weights_
Y_weights = cca.y_weights_

print("\nLoadings for Psychological Variables:")
for i, var in enumerate(X.columns):
    print(f"  {var}: {X_weights[i][0]:.4f}")

print("\nLoadings for Academic Variables:")
for i, var in enumerate(Y.columns):
    print(f"  {var}: {Y_weights[i][0]:.4f}")
```

```
Loadings for Psychological Variables:
  locus_of_control: 0.8775
  self_concept: -0.1957
  motivation: 0.4378

Loadings for Academic Variables:
  read: 0.5929
  write: 0.7631
  math: 0.2486
  science: -0.0656
```

Interpretation: The canonical correlation analysis produced a correlation of 0.4588, indicating a moderate positive relationship between the psychological and academic variable sets.
For the psychological variables, locus of control had the highest positive weight (0.8775), making it the most influential contributor, followed by motivation (0.4378).
In contrast, self-concept showed a small negative weight (–0.1957), suggesting a minimal inverse contribution.
For the academic variables, writing had the strongest positive weight (0.7631), followed by reading (0.5929) and math (0.2486), while science had a very small negative weight (–0.0656), indicating negligible influence.
Overall, the findings suggest that higher **locus of control** and **motivation** are moderately associated with better performance in **writing and reading** skills.