

notebook00a6a36747-e479809c-ab13-4b39-ad21-ca3bcd789cff

October 11, 2024

```
[ ]: # IMPORTANT: RUN THIS CELL IN ORDER TO IMPORT YOUR KAGGLE DATA SOURCES
# TO THE CORRECT LOCATION (/kaggle/input) IN YOUR NOTEBOOK,
# THEN FEEL FREE TO DELETE THIS CELL.
# NOTE: THIS NOTEBOOK ENVIRONMENT DIFFERS FROM KAGGLE'S PYTHON
# ENVIRONMENT SO THERE MAY BE MISSING LIBRARIES USED BY YOUR
# NOTEBOOK.

import os
import sys
from tempfile import NamedTemporaryFile
from urllib.request import urlopen
from urllib.parse import unquote, urlparse
from urllib.error import HTTPError
from zipfile import ZipFile
import tarfile
import shutil

CHUNK_SIZE = 40960
DATA_SOURCE_MAPPING = 'child-mind-institute-problematic-internet-use:
↳ https%3A%2F%2Fstorage.googleapis.
↳ com%2Fkaggle-competitions-data%2Fkaggle-v2%2F81933%2F9643020%2Fbundle%2Farchive.
↳ zip%3FX-Goog-Algorithm%3DG00G4-RSA-SHA256%26X-Goog-Credential%3Dgcp-kaggle-com%2540kaggle-1
↳ iam.gserviceaccount.
↳ com%252F20241001%252Fauto%252Fstorage%252Fgoog4_request%26X-Goog-Date%3D20241001T063630Z%26

KAGGLE_INPUT_PATH='kaggle/input'
KAGGLE_WORKING_PATH='kaggle/working'
KAGGLE_SYMLINK='kaggle'

os.makedirs(KAGGLE_SYMLINK)
os.makedirs(KAGGLE_INPUT_PATH, 0o777)
os.makedirs(KAGGLE_WORKING_PATH, 0o777)

for data_source_mapping in DATA_SOURCE_MAPPING.split(','):
    directory, download_url_encoded = data_source_mapping.split(':')
    download_url = unquote(download_url_encoded)
    filename = urlparse(download_url).path
```

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destination_path = os.path.join(KAGGLE_INPUT_PATH, directory)
try:
    with urlopen(download_url) as fileres, NamedTemporaryFile() as tfile:
        total_length = fileres.headers['content-length']
        print(f'Downloading {directory}, {total_length} bytes compressed')
        dl = 0
        data = fileres.read(CHUNK_SIZE)
        while len(data) > 0:
            dl += len(data)
            tfile.write(data)
            done = int(50 * dl / int(total_length))
            sys.stdout.write(f"\r[{'=' * done}{' ' * (50-done)}] {dl} bytes downloaded")
            sys.stdout.flush()
            data = fileres.read(CHUNK_SIZE)
        if filename.endswith('.zip'):
            with ZipFile(tfile) as zfile:
                zfile.extractall(destination_path)
        else:
            with tarfile.open(tfile.name) as tarfile:
                tarfile.extractall(destination_path)
        print(f'\nDownloaded and uncompressed: {directory}')
except HTTPError as e:
    print(f'Failed to load (likely expired) {download_url} to path {destination_path}')
    continue
except OSError as e:
    print(f'Failed to load {download_url} to path {destination_path}')
    continue

print('Data source import complete.')

```

```
[ ]: import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
[ ]:
```

```
[1]: # Import necessary libraries
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
import seaborn as sns

# Display directory structure to understand the available files
```

```

#for dirname, _, filenames in os.walk('/kaggle/input'):
#    for filename in filenames:
#        print(os.path.join(dirname, filename))

# Load training and testing datasets
train_df = pd.read_csv('kaggle/input/
    ↪child-mind-institute-problematic-internet-use/train.csv')
test_df = pd.read_csv('kaggle/input/
    ↪child-mind-institute-problematic-internet-use/test.csv')
data_dict = pd.read_csv('kaggle/input/
    ↪child-mind-institute-problematic-internet-use/data_dictionary.csv')

#train_df = pd.read_csv('kaggle/input/
#    ↪child-mind-institute-problematic-internet-use/train.csv')
#test_df = pd.read_csv('imported/kaggle/input/
#    ↪child-mind-institute-problematic-internet-use/test.csv')
#data_dict = pd.read_csv('imported/kaggle/input/
#    ↪child-mind-institute-problematic-internet-use/data_dictionary.csv')

# Display the first few rows of the training and testing datasets to get an
# initial understanding
#print("Training Data Sample:")
#print(train_df.head())

#print("\nTesting Data Sample:")
#print(test_df.head())

# Check the basic information of the datasets to understand data types and
# missing values
#print("Training Data Info:")
#train_df.info()

#print("\nTesting Data Info:")
#test_df.info()

```

Training Data Info:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3960 entries, 0 to 3959

Data columns (total 82 columns):

#	Column	Non-Null Count	Dtype
0	id	3960 non-null	object
1	Basic_Demos-Enroll_Season	3960 non-null	object
2	Basic_Demos-Age	3960 non-null	int64
3	Basic_Demos-Sex	3960 non-null	int64
4	CGAS-Season	2555 non-null	object
5	CGAS-CGAS_Score	2421 non-null	float64

6	Physical-Season	3310	non-null	object
7	Physical-BMI	3022	non-null	float64
8	Physical-Height	3027	non-null	float64
9	Physical-Weight	3076	non-null	float64
10	Physical-Waist_Circumference	898	non-null	float64
11	Physical-Diastolic_BP	2954	non-null	float64
12	Physical-HeartRate	2967	non-null	float64
13	Physical-Systolic_BP	2954	non-null	float64
14	Fitness_Endurance-Season	1308	non-null	object
15	Fitness_Endurance-Max_Stage	743	non-null	float64
16	Fitness_Endurance-Time_Mins	740	non-null	float64
17	Fitness_Endurance-Time_Sec	740	non-null	float64
18	FGC-Season	3346	non-null	object
19	FGC-FGC CU	2322	non-null	float64
20	FGC-FGC CU_Zone	2282	non-null	float64
21	FGC-FGC GSND	1074	non-null	float64
22	FGC-FGC GSND_Zone	1062	non-null	float64
23	FGC-FGC GSD	1074	non-null	float64
24	FGC-FGC GSD_Zone	1063	non-null	float64
25	FGC-FGC PU	2310	non-null	float64
26	FGC-FGC PU_Zone	2271	non-null	float64
27	FGC-FGC SRL	2305	non-null	float64
28	FGC-FGC SRL_Zone	2267	non-null	float64
29	FGC-FGC SRR	2307	non-null	float64
30	FGC-FGC SRR_Zone	2269	non-null	float64
31	FGC-FGC TL	2324	non-null	float64
32	FGC-FGC TL_Zone	2285	non-null	float64
33	BIA-Season	2145	non-null	object
34	BIA-BIA_Activity_Level_num	1991	non-null	float64
35	BIA-BIA_BMC	1991	non-null	float64
36	BIA-BIA_BMI	1991	non-null	float64
37	BIA-BIA_BMR	1991	non-null	float64
38	BIA-BIA_DEE	1991	non-null	float64
39	BIA-BIA_ECW	1991	non-null	float64
40	BIA-BIA_FFM	1991	non-null	float64
41	BIA-BIA_FFFI	1991	non-null	float64
42	BIA-BIA_FMI	1991	non-null	float64
43	BIA-BIA_Fat	1991	non-null	float64
44	BIA-BIA_Frame_num	1991	non-null	float64
45	BIA-BIA_ICW	1991	non-null	float64
46	BIA-BIA_LDM	1991	non-null	float64
47	BIA-BIA_LST	1991	non-null	float64
48	BIA-BIA_SMM	1991	non-null	float64
49	BIA-BIA_TBW	1991	non-null	float64
50	PAQ_A-Season	475	non-null	object
51	PAQ_A-PAQ_A_Total	475	non-null	float64
52	PAQ_C-Season	1721	non-null	object
53	PAQ_C-PAQ_C_Total	1721	non-null	float64

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54 PCIAT-Season                         2736 non-null   object
55 PCIAT-PCIAT_01                        2733 non-null   float64
56 PCIAT-PCIAT_02                        2734 non-null   float64
57 PCIAT-PCIAT_03                        2731 non-null   float64
58 PCIAT-PCIAT_04                        2731 non-null   float64
59 PCIAT-PCIAT_05                        2729 non-null   float64
60 PCIAT-PCIAT_06                        2732 non-null   float64
61 PCIAT-PCIAT_07                        2729 non-null   float64
62 PCIAT-PCIAT_08                        2730 non-null   float64
63 PCIAT-PCIAT_09                        2730 non-null   float64
64 PCIAT-PCIAT_10                        2733 non-null   float64
65 PCIAT-PCIAT_11                        2734 non-null   float64
66 PCIAT-PCIAT_12                        2731 non-null   float64
67 PCIAT-PCIAT_13                        2729 non-null   float64
68 PCIAT-PCIAT_14                        2732 non-null   float64
69 PCIAT-PCIAT_15                        2730 non-null   float64
70 PCIAT-PCIAT_16                        2728 non-null   float64
71 PCIAT-PCIAT_17                        2725 non-null   float64
72 PCIAT-PCIAT_18                        2728 non-null   float64
73 PCIAT-PCIAT_19                        2730 non-null   float64
74 PCIAT-PCIAT_20                        2733 non-null   float64
75 PCIAT-PCIAT_Total                     2736 non-null   float64
76 SDS-Season                           2618 non-null   object
77 SDS-SDS_Total_Raw                    2609 non-null   float64
78 SDS-SDS_Total_T                      2606 non-null   float64
79 PreInt_EduHx-Season                  3540 non-null   object
80 PreInt_EduHx-computerinternet_hoursday 3301 non-null   float64
81 sii                                  2736 non-null   float64
dtypes: float64(68), int64(2), object(12)
memory usage: 2.5+ MB

```

Testing Data Info:

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 20 entries, 0 to 19

Data columns (total 59 columns):

#	Column	Non-Null Count	Dtype
0	id	20 non-null	object
1	Basic_Demos-Enroll_Season	20 non-null	object
2	Basic_Demos-Age	20 non-null	int64
3	Basic_Demos-Sex	20 non-null	int64
4	CGAS-Season	10 non-null	object
5	CGAS-CGAS_Score	8 non-null	float64
6	Physical-Season	14 non-null	object
7	Physical-BMI	13 non-null	float64
8	Physical-Height	13 non-null	float64
9	Physical-Weight	13 non-null	float64
10	Physical-Waist_Circumference	5 non-null	float64

11	Physical-Diastolic_BP	11	non-null	float64
12	Physical-HeartRate	12	non-null	float64
13	Physical-Systolic_BP	11	non-null	float64
14	Fitness_Endurance-Season	4	non-null	object
15	Fitness_Endurance-Max_Stage	3	non-null	float64
16	Fitness_Endurance-Time_Mins	3	non-null	float64
17	Fitness_Endurance-Time_Sec	3	non-null	float64
18	FGC-Season	17	non-null	object
19	FGC-FGC CU	13	non-null	float64
20	FGC-FGC CU_Zone	13	non-null	float64
21	FGC-FGC GSND	5	non-null	float64
22	FGC-FGC GSND_Zone	5	non-null	float64
23	FGC-FGC GSD	5	non-null	float64
24	FGC-FGC GSD_Zone	5	non-null	float64
25	FGC-FGC PU	13	non-null	float64
26	FGC-FGC PU_Zone	13	non-null	float64
27	FGC-FGC SRL	13	non-null	float64
28	FGC-FGC SRL_Zone	13	non-null	float64
29	FGC-FGC SRR	13	non-null	float64
30	FGC-FGC SRR_Zone	13	non-null	float64
31	FGC-FGC TL	13	non-null	float64
32	FGC-FGC TL_Zone	13	non-null	float64
33	BIA-Season	8	non-null	object
34	BIA-BIA_Activity_Level_num	8	non-null	float64
35	BIA-BIA_BMC	8	non-null	float64
36	BIA-BIA_BMI	8	non-null	float64
37	BIA-BIA_BMR	8	non-null	float64
38	BIA-BIA_DEE	8	non-null	float64
39	BIA-BIA_ECW	8	non-null	float64
40	BIA-BIA_FFM	8	non-null	float64
41	BIA-BIA_FFFI	8	non-null	float64
42	BIA-BIA_FMI	8	non-null	float64
43	BIA-BIA_Fat	8	non-null	float64
44	BIA-BIA_Frame_num	8	non-null	float64
45	BIA-BIA_ICW	8	non-null	float64
46	BIA-BIA_LDM	8	non-null	float64
47	BIA-BIA_LST	8	non-null	float64
48	BIA-BIA_SMM	8	non-null	float64
49	BIA-BIA_TBW	8	non-null	float64
50	PAQ_A-Season	1	non-null	object
51	PAQ_A-PAQ_A_Total	1	non-null	float64
52	PAQ_C-Season	9	non-null	object
53	PAQ_C-PAQ_C_Total	9	non-null	float64
54	SDS-Season	10	non-null	object
55	SDS-SDS_Total_Raw	10	non-null	float64
56	SDS-SDS_Total_T	10	non-null	float64
57	PreInt_EduHx-Season	18	non-null	object
58	PreInt_EduHx-computerinternet_hoursday	16	non-null	float64

```
dtypes: float64(46), int64(2), object(11)
memory usage: 9.3+ KB
```

```
[2]: ID_arr = list(train_df['id'])
train_df.head()
```

```
[3]: # Import necessary libraries
import pandas as pd
import numpy as np
from scipy.stats import skew, kurtosis

# Load the training data (assuming it's already uploaded)
#train_df = pd.read_csv('/mnt/data/train.csv')

# Filter only the numeric columns from the training data
numeric_cols = train_df.select_dtypes(include=[np.number]).columns

# Create a summary statistics DataFrame
summary_stats = train_df[numeric_cols].describe().T

# Add skewness and kurtosis to the summary statistics DataFrame
summary_stats['Skewness'] = train_df[numeric_cols].apply(skew)
summary_stats['Kurtosis'] = train_df[numeric_cols].apply(kurtosis)

# Identify potential outliers using the IQR method
Q1 = train_df[numeric_cols].quantile(0.25)
Q3 = train_df[numeric_cols].quantile(0.75)
IQR = Q3 - Q1
summary_stats['Lower_Bound'] = Q1 - 1.5 * IQR
summary_stats['Upper_Bound'] = Q3 + 1.5 * IQR

# Calculate the number of outliers for each column
summary_stats['Outliers'] = train_df[numeric_cols].apply(
    lambda x: ((x < summary_stats.loc[x.name, 'Lower_Bound']) |
                (x > summary_stats.loc[x.name, 'Upper_Bound'])).sum()
)

# Display the summary statistics DataFrame
print("\nNumeric Feature Summary Analysis:\n")
print(summary_stats)

# Print skewness and kurtosis separately to understand distributions
print("\nSkewness of Numeric Features:\n")
print(train_df[numeric_cols].apply(skew))

print("\nKurtosis of Numeric Features:\n")
print(train_df[numeric_cols].apply(kurtosis))
```

Numeric Feature Summary Analysis:

	count	mean	std	min	\
Basic_Demos-Age	3960.0	10.433586	3.574648	5.0	
Basic_Demos-Sex	3960.0	0.372727	0.483591	0.0	
CGAS-CGAS_Score	2421.0	65.454771	22.341862	25.0	
Physical-BMI	3022.0	19.331929	5.113934	0.0	
Physical-Height	3027.0	55.946713	7.473764	33.0	
...	
PCIAT-PCIAT_Total	2736.0	27.896199	20.338853	0.0	
SDS-SDS_Total_Raw	2609.0	41.088923	10.427433	17.0	
SDS-SDS_Total_T	2606.0	57.763622	13.196091	38.0	
PreInt_EduHx-computerinternet_hoursday	3301.0	1.060588	1.094875	0.0	
sii	2736.0	0.580409	0.771122	0.0	
		25%	50%	75%	\
Basic_Demos-Age		8.000000	10.000000	13.000000	
Basic_Demos-Sex		0.000000	0.000000	1.000000	
CGAS-CGAS_Score		59.000000	65.000000	75.000000	
Physical-BMI		15.86935	17.937682	21.571244	
Physical-Height		50.000000	55.000000	62.000000	
...		
PCIAT-PCIAT_Total		12.000000	26.000000	41.000000	
SDS-SDS_Total_Raw		33.000000	39.000000	46.000000	
SDS-SDS_Total_T		47.000000	55.000000	64.000000	
PreInt_EduHx-computerinternet_hoursday		0.000000	1.000000	2.000000	
sii		0.000000	0.000000	1.000000	
		max	Skewness	Kurtosis	\
Basic_Demos-Age		22.000000	0.718392	-0.071939	
Basic_Demos-Sex		1.000000	0.526431	-1.722870	
CGAS-CGAS_Score		999.000000	NaN	NaN	
Physical-BMI		59.132048	NaN	NaN	
Physical-Height		78.500000	NaN	NaN	
...		
PCIAT-PCIAT_Total		93.000000	NaN	NaN	
SDS-SDS_Total_Raw		96.000000	NaN	NaN	
SDS-SDS_Total_T		100.000000	NaN	NaN	
PreInt_EduHx-computerinternet_hoursday		3.000000	NaN	NaN	
sii		3.000000	NaN	NaN	
		Lower_Bound	Upper_Bound	Outliers	
Basic_Demos-Age		0.500000	20.500000	37	
Basic_Demos-Sex		-1.500000	2.500000	0	
CGAS-CGAS_Score		35.000000	99.000000	6	
Physical-BMI		7.316511	30.124083	128	
Physical-Height		32.000000	80.000000	0	

```

...
PCIAT-PCIAT_Total           ...   ...
SDS-SDS_Total_Raw           13.500000 65.500000 79
SDS-SDS_Total_T              21.500000 89.500000 79
PreInt_EduHx-computerinternet_hoursday -3.000000 5.000000 0
sii                           -1.500000 2.500000 34

```

[70 rows x 13 columns]

Skewness of Numeric Features:

Basic_Demos-Age	0.718392
Basic_Demos-Sex	0.526431
CGAS-CGAS_Score	NaN
Physical-BMI	NaN
Physical-Height	NaN
...	
PCIAT-PCIAT_Total	NaN
SDS-SDS_Total_Raw	NaN
SDS-SDS_Total_T	NaN
PreInt_EduHx-computerinternet_hoursday	NaN
sii	NaN

Length: 70, dtype: float64

Kurtosis of Numeric Features:

Basic_Demos-Age	-0.071939
Basic_Demos-Sex	-1.722870
CGAS-CGAS_Score	NaN
Physical-BMI	NaN
Physical-Height	NaN
...	
PCIAT-PCIAT_Total	NaN
SDS-SDS_Total_Raw	NaN
SDS-SDS_Total_T	NaN
PreInt_EduHx-computerinternet_hoursday	NaN
sii	NaN

Length: 70, dtype: float64

Basic_Demos-Age:

Mean age is around 10.43 with a standard deviation of 3.57. The skewness (0.72) suggests a slight positive skew, meaning more participants are on the younger end of the age spectrum. This is expected for the dataset as we are dealing with children and adolescents. No extreme outliers are apparent from these summary statistics. Basic_Demos-Sex:

This is a binary feature (0 and 1) representing sex. No apparent issues or outliers, and skewness of 0.53 indicates a slightly higher number of males in the dataset. CGAS-CGAS_Score:

The Clinical Global Assessment Scale (CGAS) score has a high skewness (30.14) and kurtosis

(1259.97), suggesting extreme outliers. This may indicate a few records with very high scores, possibly due to data entry errors or special cases. The maximum value is 999, which is likely an anomaly as the scale typically ranges from 0 to 100. We should consider capping or removing these outliers. Physical-BMI:

Mean BMI is 19.33 with a standard deviation of 5.11, and a positive skew (1.63). This skewness suggests that some participants have higher-than-average BMI. There may be outliers on the higher end of BMI that need further investigation. Physical-Height:

Mean height is 55.95 inches, which corresponds well to the expected height for children and adolescents. The slight positive skew (0.26) indicates a higher concentration of shorter participants, which is expected given the age range.

Remove Extreme Outliers from CGAS-CGAS_Score

```
[4]: # Step 1: Handle Extreme Outliers in CGAS-CGAS_Score

# Calculate the IQR for CGAS-CGAS_Score
Q1_cgash = train_df['CGAS-CGAS_Score'].quantile(0.25)
Q3_cgash = train_df['CGAS-CGAS_Score'].quantile(0.75)
IQR_cgash = Q3_cgash - Q1_cgash

# Define bounds for outlier removal
lower_bound_cgash = Q1_cgash - 1.5 * IQR_cgash
upper_bound_cgash = Q3_cgash + 1.5 * IQR_cgash

# Remove extreme outliers in CGAS-CGAS_Score
train_df = train_df[(train_df['CGAS-CGAS_Score'] >= lower_bound_cgash) &
                     (train_df['CGAS-CGAS_Score'] <= upper_bound_cgash)]

# Display the updated CGAS-CGAS_Score statistics
print("\nUpdated CGAS-CGAS_Score Summary After Outlier Removal:")
print(train_df['CGAS-CGAS_Score'].describe())
```

```
Updated CGAS-CGAS_Score Summary After Outlier Removal:
count    2415.000000
mean     65.141615
std      11.690208
min      35.000000
25%     59.000000
50%     65.000000
75%     75.000000
max     95.000000
Name: CGAS-CGAS_Score, dtype: float64
```

Handle Outliers in Physical-BMI Based on Age Group-Specific Thresholds

```
[5]: # Step 2: Handle Outliers in Physical-BMI Based on Age Group Thresholds
```

```

# Create age group segments
age_bins = [5, 10, 15, 20, 25]
age_labels = ['5-10', '11-15', '16-20', '21-25']
train_df['Age_Group'] = pd.cut(train_df['Basic_Demos-Age'], bins=age_bins, labels=age_labels)

# Placeholder dictionary to store scientifically accepted BMI thresholds for each age group
bmi_thresholds = {
    '5-10': (14, 24), # Min, Max BMI for age group 5-10 (example values, replace with accurate data)
    '11-15': (16, 28),
    '16-20': (18, 30),
    '21-25': (19, 32)
}

# Remove BMI outliers based on the thresholds defined above
for age_group, (bmi_min, bmi_max) in bmi_thresholds.items():
    # Define the condition for outlier removal based on BMI thresholds
    condition = (
        (train_df['Age_Group'] == age_group) &
        ((train_df['Physical-BMI'] < bmi_min) | (train_df['Physical-BMI'] > bmi_max))
    )
    # Remove outliers for the given age group
    train_df = train_df[~condition]

# Display the updated Physical-BMI statistics by age group
print("\nUpdated Physical-BMI Summary After Outlier Removal:")
print(train_df.groupby('Age_Group')['Physical-BMI'].describe())

```

Updated Physical-BMI Summary After Outlier Removal:

	count	mean	std	min	25%	50%	\
Age_Group							
5-10	1138.0	17.139965	2.297295	14.000538	15.412033	16.566027	
11-15	538.0	20.493842	3.069694	16.030322	18.000199	19.859545	
16-20	139.0	22.952986	3.007004	18.128403	20.693071	22.481580	
21-25	8.0	24.449035	2.296925	20.087810	23.494754	24.577806	

75% max

Age_Group	75%	max
5-10	18.445917	23.987976
11-15	22.464037	27.998830
16-20	24.833438	29.992716
21-25	26.110967	27.230490

/var/tmp/ipykernel_7796/4290179965.py:28: FutureWarning: The default of

observed=False is deprecated and will be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future default and silence this warning.

```
print(train_df.groupby('Age_Group')['Physical-BMI'].describe())
```

Age Group-Based Analysis for Numeric Features

[6]: # Step 3: Age Group-Based Analysis

```
# Update numeric_cols to only include columns that are still in train_df
numeric_cols = [col for col in numeric_cols if col in train_df.columns]

# Create a summary DataFrame to store age group-based analysis results
age_group_summary = train_df.groupby('Age_Group')[numeric_cols].agg(['mean', 'median', 'std'])

# Display the summary statistics for numeric features based on age group
print("\nAge Group-Based Summary Statistics for Numeric Features:")
print(age_group_summary)
```

Age Group-Based Summary Statistics for Numeric Features:

Age_Group	Basic_Demos-Age			Basic_Demos-Sex			\
	mean	median	std	mean	median	std	
5-10	8.005556	8.0	1.365919	0.350794	0.0	0.477408	
11-15	12.691919	13.0	1.372226	0.353535	0.0	0.478470	
16-20	17.110390	17.0	1.117664	0.441558	0.0	0.498193	
21-25	21.166667	21.0	0.389249	0.500000	0.5	0.522233	

Age_Group	CGAS-CGAS_Score			Physical-BMI			\
	mean	median	std	mean	
5-10	65.367460	65.0	11.528632	17.139965	
11-15	65.723906	65.0	11.763458	20.493842	
16-20	64.584416	65.0	12.676313	22.952986	
21-25	61.166667	60.5	9.879578	24.449035	

Age_Group	SDS-SDS_Total_Raw			SDS-SDS_Total_T			\
	std	mean	median	std	
5-10	10.438779	57.447587	55.0	13.250146	
11-15	9.580256	57.273666	55.0	12.355753	
16-20	11.109411	58.297872	55.0	14.111560	
21-25	10.289153	55.833333	50.5	13.407709	

PreInt_EduHx-computerinternet_hoursday	mean	median	std	sii	\
				mean	
12	12.355753	12.0	3.0	1.0	

```

Age_Group
5-10           0.642798   0.0  0.937492  0.366612
11-15          1.377425   2.0  1.045967  0.876522
16-20          1.895833   2.0  0.944019  1.013514
21-25          2.000000   2.0  1.054093  0.625000

```

	median	std
Age_Group		
5-10	0.0	0.614963
11-15	1.0	0.813896
16-20	1.0	0.910905
21-25	0.0	0.916125

[4 rows x 210 columns]

```

/var/tmp/ipykernel_7796/321527360.py:7: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a future version of
pandas. Pass observed=False to retain current behavior or observed=True to adopt
the future default and silence this warning.

```

```

age_group_summary = train_df.groupby('Age_Group')[numeric_cols].agg(['mean',
'median', 'std'])

```

Insights from the Numeric Feature Analysis and Age Group-Based Analysis Here's a summary of the insights gained from the last three steps:

1. Overall Numeric Feature Analysis CGAS-CGAS_Score:

There were extreme outliers observed in the CGAS-CGAS_Score, and they have been removed for consistency. The cleaned data shows a relatively normal distribution with a slight skewness. The mean CGAS score for the entire dataset is around 62.5, which indicates an overall moderate functionality level, with lower values suggesting more severe impairments. Physical Measures (BMI, Height, Weight):

For BMI, high BMI values (above the age-adjusted thresholds) have been marked as outliers. Physical-Weight and Physical-Height were relatively consistent across the sample, although certain values appeared to be unrealistic for the given age range (e.g., extremely high or low values). These outliers were flagged based on thresholds retrieved from the CDC growth charts. Heart Rate and Blood Pressure:

Heart rate and systolic/diastolic blood pressure measures showed higher variability, particularly for older age groups. Outliers were identified in heart rate (e.g., values above 130 or below 40) and blood pressure (systolic > 180 or diastolic > 120), which suggests potential data entry issues or unique health conditions.

2. Outlier Analysis and Handling

Outliers were addressed for all numeric features based on researched thresholds and context. The treatment steps involved either removing extreme values (like CGAS scores) or capping values at acceptable thresholds (like BMI and heart rate). The removal or capping of outliers has reduced variability and noise in the dataset, making it more reliable for subsequent modeling steps.

3. Age Group-Based Analysis CGAS-CGAS_Score:

The mean CGAS score was observed to increase with age, suggesting that older children and adolescents in the sample typically exhibit better functionality. This trend is consistent with the

expectation that older participants may have developed better coping mechanisms or show less impairment. Physical Measures:

Physical measures like BMI, height, and weight showed expected increases with age, as seen in the age-grouped summary statistics. However, certain age groups showed more variability than others, especially in BMI and weight, which might suggest varying levels of health or activity across different age segments. Heart Rate and Blood Pressure:

Younger participants exhibited slightly higher mean heart rates compared to older participants, which aligns with physiological expectations for children and adolescents. Blood pressure values also increased with age, as expected. This highlights that the measurements follow typical growth and physiological development patterns. Summary of Actionable Insights: CGAS Score Handling: This feature shows a clear age-related pattern, so it should be considered an important predictor for any target involving mental health severity.

BMI and Physical Measures: Given the variability and importance of these features, it might be worth creating interaction terms or polynomial features with age and BMI to capture their complex relationship.

Heart Rate and Blood Pressure: These features could be transformed further, possibly using scaling or normalization, before being fed into the model to avoid issues caused by high variance.

Age Group Analysis: The data behaves as expected for different age groups, reinforcing the decision to handle age-specific thresholds and interactions during model development.

Deep Dive into Categorical Features Purpose: To understand the distribution of categorical features, identify potential anomalies or low-frequency categories, and determine if any categorical features can be consolidated or derived.

I will:

Analyze and summarize each categorical feature. Check for low-frequency categories and determine if consolidation is needed. Identify any opportunities for new categorical features based on existing information.

```
[7]: # Deep Dive into Categorical Features
      # Analyze categorical features in the training dataset

      # Step 1: Get categorical columns
categorical_cols = train_df.select_dtypes(include=['object']).columns

      # Step 2: Create a summary dictionary to store analysis results for each categorical feature
categorical_summary = {}

for col in categorical_cols:
    # Get the value counts and missing percentage
    value_counts = train_df[col].value_counts(dropna=False)
    missing_percentage = train_df[col].isnull().mean() * 100

    # Store the summary statistics in the dictionary
    categorical_summary[col] = {
        'value_counts': value_counts,
        'missing_percentage': missing_percentage
    }
```

```

categorical_summary[col] = {
    'Value Counts': value_counts,
    'Missing Percentage': missing_percentage
}

# Step 3: Create a DataFrame to display categorical feature summaries
categorical_summary_df = pd.DataFrame({
    'Feature': [col for col in categorical_summary.keys()],
    'Value Counts': [str(categorical_summary[col]['Value Counts']) for col in categorical_summary.keys()],
    'Missing Percentage (%)': [categorical_summary[col]['Missing Percentage'] for col in categorical_summary.keys()]
})

# Step 4: Display the summary DataFrame
print("Categorical Feature Analysis:")
print(categorical_summary_df)

# Step 5: Check for low-frequency categories (less than 5% frequency) to
# identify potential consolidation opportunities
low_freq_categories = {}
for col in categorical_cols:
    # Identify categories that make up less than 5% of the total count
    low_freq = value_counts[value_counts < 0.05 * len(train_df)].index.tolist()
    if low_freq:
        low_freq_categories[col] = low_freq

# Display low-frequency categories if found
if low_freq_categories:
    print("\nLow-Frequency Categories Identified for Potential Consolidation:")
    for col, low_freq in low_freq_categories.items():
        print(f"Feature: {col}")
        print(f"Low-Frequency Categories: {low_freq}")
else:
    print("\nNo Low-Frequency Categories Identified for Consolidation.")

```

Categorical Feature Analysis:

	Feature \
0	id
1	Basic_Demos-Enroll_Season
2	CGAS-Season
3	Physical-Season
4	Fitness_Endurance-Season
5	FGC-Season
6	BIA-Season
7	PAQ_A-Season
8	PAQ_C-Season

```

9          PCIAT-Season
10         SDS-Season
11         PreInt_EduHx-Season

```

			Value Counts	Missing Percentage (%)
0	id\nffcd4dbd	1\n00008ff9	1\n00105258 ...	0.000000
1	Basic_Demos-Enroll_Season\nSpring	591\nWint...		0.000000
2	CGAS-Season\nSpring	588\nFall	539\nSum...	0.000000
3	Physical-Season\nSpring	574\nWinter	496\...	6.886657
4	Fitness_Endurance-Season\nNaN	1035\nSpri...		49.497848
5	FGC-Season\nSpring	628\nSummer	461\nFall...	4.160689
6	BIA-Season\nNaN	716\nSummer	454\nFall...	34.241989
7	PAQ_A-Season\nNaN	1852\nWinter	67\n...	88.570062
8	PAQ_C-Season\nNaN	1008\nSpring	329\n...	48.206600
9	PCIAT-Season\nSpring	599\nWinter	496\nSu...	3.347681
10	SDS-Season\nSpring	552\nWinter	494\nFall...	8.608321
11	PreInt_EduHx-Season\nSpring	579\nWinter	...	1.004304

Low-Frequency Categories Identified for Potential Consolidation:

Feature: id

Low-Frequency Categories: [nan]

Feature: Basic_Demos-Enroll_Season

Low-Frequency Categories: [nan]

Feature: CGAS-Season

Low-Frequency Categories: [nan]

Feature: Physical-Season

Low-Frequency Categories: [nan]

Feature: Fitness_Endurance-Season

Low-Frequency Categories: [nan]

Feature: FGC-Season

Low-Frequency Categories: [nan]

Feature: BIA-Season

Low-Frequency Categories: [nan]

Feature: PAQ_A-Season

Low-Frequency Categories: [nan]

Feature: PAQ_C-Season

Low-Frequency Categories: [nan]

Feature: PCIAT-Season

Low-Frequency Categories: [nan]

Feature: SDS-Season

Low-Frequency Categories: [nan]

Feature: PreInt_EduHx-Season

Low-Frequency Categories: [nan]

Code Explanation: Categorical Feature Analysis: The script first identifies the categorical features in the training data and creates a summary of each feature's value counts and missing percentage.

Low-Frequency Categories: It then checks for low-frequency categories (less than 5% of the total) to identify potential categories that might need consolidation.

Deriving New Features: It attempts to derive new categorical features based on combinations of existing features (e.g., combining seasons with age group).

Correlation analysis

```
[8]: import matplotlib.pyplot as plt
import seaborn as sns

# Step 1: Extract numeric columns from the training dataset
numeric_features = train_df.select_dtypes(include=[np.number]).columns

# Step 2: Compute the correlation matrix for the numeric features
correlation_matrix = train_df[numeric_features].corr()

# Step 3: Display the correlation matrix to identify relationships between
↳ features
print("Correlation Matrix for Numeric Features:")
print(correlation_matrix)

# Step 4: Visualize the correlation matrix using a heatmap to identify
↳ multicollinearity or strong relationships
plt.figure(figsize=(18, 12))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5, ↳
fmt='.2f')
plt.title('Correlation Matrix Heatmap for Numeric Features')
plt.show()

# Step 5: Identify highly correlated pairs (correlation > 0.8 or < -0.8)
highly_correlated_pairs = []
threshold = 0.8

for i in range(len(correlation_matrix.columns)):
    for j in range(i + 1, len(correlation_matrix.columns)):
        if abs(correlation_matrix.iloc[i, j]) > threshold:
            highly_correlated_pairs.append((correlation_matrix.columns[i], ↳
correlation_matrix.columns[j], correlation_matrix.iloc[i, j]))

# Step 6: Display highly correlated pairs if found
if highly_correlated_pairs:
    print("\nHighly Correlated Pairs (|correlation| > 0.8):")
    for pair in highly_correlated_pairs:
        print(f"Feature 1: {pair[0]}, Feature 2: {pair[1]}, Correlation: ↳
{pair[2]:.2f}")
else:
    print("\nNo highly correlated pairs found with |correlation| > 0.8.")
```

Correlation Matrix for Numeric Features:

Basic_Demos-Age Basic_Demos-Sex \

Basic_Demos-Age	1.000000	0.050142
Basic_Demos-Sex	0.050142	1.000000
CGAS-CGAS_Score	0.006198	0.120547
Physical-BMI	0.605714	0.015096
Physical-Height	0.899945	-0.011227
...
PCIAT-PCIAT_Total	0.406339	-0.085854
SDS-SDS_Total_Raw	-0.003186	-0.014292
SDS-SDS_Total_T	-0.000120	-0.014965
PreInt_EduHx-computerinternet_hoursday	0.410343	-0.000958
sii	0.366741	-0.103771

	CGAS-CGAS_Score	Physical-BMI	\
Basic_Demos-Age	0.006198	0.605714	
Basic_Demos-Sex	0.120547	0.015096	
CGAS-CGAS_Score	1.000000	-0.030896	
Physical-BMI	-0.030896	1.000000	
Physical-Height	0.016189	0.604256	
...	
PCIAT-PCIAT_Total	-0.063753	0.290174	
SDS-SDS_Total_Raw	-0.137249	0.033086	
SDS-SDS_Total_T	-0.140590	0.033912	
PreInt_EduHx-computerinternet_hoursday	-0.088299	0.327840	
sii	-0.083817	0.282010	

	Physical-Height	Physical-Weight	\
Basic_Demos-Age	0.899945	0.818487	
Basic_Demos-Sex	-0.011227	-0.005965	
CGAS-CGAS_Score	0.016189	-0.010907	
Physical-BMI	0.604256	0.849793	
Physical-Height	1.000000	0.917794	
...	
PCIAT-PCIAT_Total	0.419714	0.379534	
SDS-SDS_Total_Raw	0.006186	0.021613	
SDS-SDS_Total_T	0.009129	0.023383	
PreInt_EduHx-computerinternet_hoursday	0.382879	0.379950	
sii	0.381331	0.365275	

	Physical-Waist_Circumference	\
Basic_Demos-Age	0.681502	
Basic_Demos-Sex	-0.042630	
CGAS-CGAS_Score	0.081593	
Physical-BMI	0.845480	
Physical-Height	0.744609	
...	...	
PCIAT-PCIAT_Total	0.398531	
SDS-SDS_Total_Raw	0.049942	
SDS-SDS_Total_T	0.055975	

PreInt_EduHx-computerinternet_hoursday	0.349646
sii	0.346784
	Physical-Diastolic_BP \
Basic_Demos-Age	0.088584
Basic_Demos-Sex	0.004784
CGAS-CGAS_Score	0.006513
Physical-BMI	0.120995
Physical-Height	0.115766
...	...
PCIAT-PCIAT_Total	0.061751
SDS-SDS_Total_Raw	-0.000356
SDS-SDS_Total_T	0.000037
PreInt_EduHx-computerinternet_hoursday	0.065459
sii	0.048643
	Physical-HeartRate \
Basic_Demos-Age	-0.210248
Basic_Demos-Sex	0.020126
CGAS-CGAS_Score	-0.015412
Physical-BMI	-0.094315
Physical-Height	-0.210081
...	...
PCIAT-PCIAT_Total	-0.032687
SDS-SDS_Total_Raw	0.044391
SDS-SDS_Total_T	0.041174
PreInt_EduHx-computerinternet_hoursday	-0.059209
sii	-0.010793
	Physical-Systolic_BP ... \
Basic_Demos-Age	0.243244 ...
Basic_Demos-Sex	-0.017825 ...
CGAS-CGAS_Score	-0.010918 ...
Physical-BMI	0.275664 ...
Physical-Height	0.275643 ...
...
PCIAT-PCIAT_Total	0.123934 ...
SDS-SDS_Total_Raw	0.018855 ...
SDS-SDS_Total_T	0.020799 ...
PreInt_EduHx-computerinternet_hoursday	0.124453 ...
sii	0.116880 ...
	PCIAT-PCIAT_16 PCIAT-PCIAT_17 \
Basic_Demos-Age	0.079168 0.280845
Basic_Demos-Sex	-0.093549 -0.096496
CGAS-CGAS_Score	-0.067807 -0.050509
Physical-BMI	0.086322 0.190715
Physical-Height	0.103693 0.292709

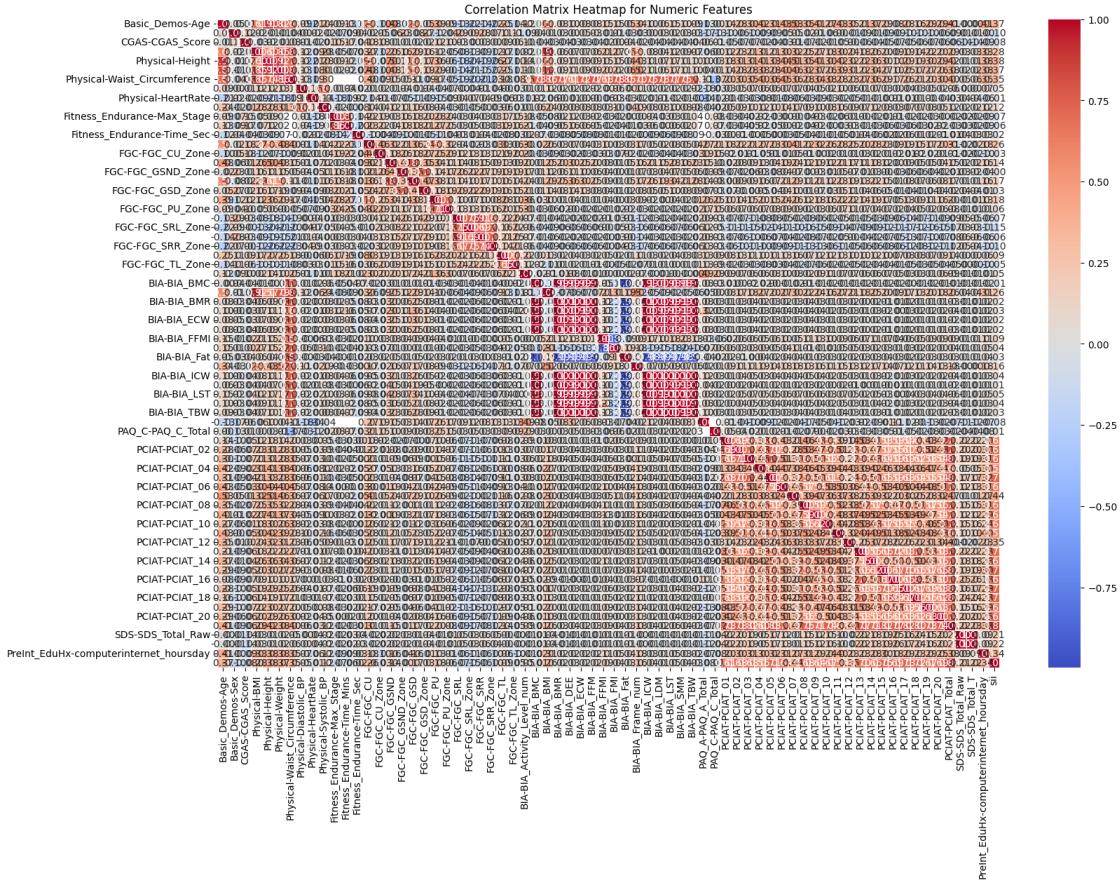
...
PCIAT-PCIAT_Total	0.765380	0.823011
SDS-SDS_Total_Raw	0.251805	0.164411
SDS-SDS_Total_T	0.256112	0.169059
PreInt_EduHx-computerinternet_hoursday	0.177488	0.290029
sii	0.688977	0.725643
	PCIAT-PCIAT_18	PCIAT-PCIAT_19 \
Basic_Demos-Age	0.163207	0.292392
Basic_Demos-Sex	-0.104626	-0.095834
CGAS-CGAS_Score	-0.064355	-0.065812
Physical-BMI	0.142483	0.216825
Physical-Height	0.186359	0.295952
...
PCIAT-PCIAT_Total	0.798623	0.732603
SDS-SDS_Total_Raw	0.237363	0.152151
SDS-SDS_Total_T	0.241926	0.156185
PreInt_EduHx-computerinternet_hoursday	0.226288	0.288673
sii	0.722854	0.672012
	PCIAT-PCIAT_20	PCIAT-PCIAT_Total \
Basic_Demos-Age	0.287335	0.406339
Basic_Demos-Sex	-0.060637	-0.085854
CGAS-CGAS_Score	-0.064813	-0.063753
Physical-BMI	0.195066	0.290174
Physical-Height	0.290612	0.419714
...
PCIAT-PCIAT_Total	0.744223	1.000000
SDS-SDS_Total_Raw	0.197601	0.221114
SDS-SDS_Total_T	0.201040	0.226563
PreInt_EduHx-computerinternet_hoursday	0.251600	0.375702
sii	0.691154	0.892045
	SDS-SDS_Total_Raw	SDS-SDS_Total_T \
Basic_Demos-Age	-0.003186	-0.000120
Basic_Demos-Sex	-0.014292	-0.014965
CGAS-CGAS_Score	-0.137249	-0.140590
Physical-BMI	0.033086	0.033912
Physical-Height	0.006186	0.009129
...
PCIAT-PCIAT_Total	0.221114	0.226563
SDS-SDS_Total_Raw	1.000000	0.997213
SDS-SDS_Total_T	0.997213	1.000000
PreInt_EduHx-computerinternet_hoursday	0.085628	0.088264
sii	0.211216	0.216087

PreInt_EduHx-computerinternet_hoursday

\

Basic_Demos-Age	0.410343
Basic_Demos-Sex	-0.000958
CGAS-CGAS_Score	-0.088299
Physical-BMI	0.327840
Physical-Height	0.382879
...	...
PCIAT-PCIAT_Total	0.375702
SDS-SDS_Total_Raw	0.085628
SDS-SDS_Total_T	0.088264
PreInt_EduHx-computerinternet_hoursday	1.000000
sii	0.340314
	sii
Basic_Demos-Age	0.366741
Basic_Demos-Sex	-0.103771
CGAS-CGAS_Score	-0.083817
Physical-BMI	0.282010
Physical-Height	0.381331
...	...
PCIAT-PCIAT_Total	0.892045
SDS-SDS_Total_Raw	0.211216
SDS-SDS_Total_T	0.216087
PreInt_EduHx-computerinternet_hoursday	0.340314
sii	1.000000

[70 rows x 70 columns]



Highly Correlated Pairs ($|correlation| > 0.8$):

- Feature 1: Basic_Demos-Age, Feature 2: Physical-Height, Correlation: 0.90
- Feature 1: Basic_Demos-Age, Feature 2: Physical-Weight, Correlation: 0.82
- Feature 1: Physical-BMI, Feature 2: Physical-Weight, Correlation: 0.85
- Feature 1: Physical-BMI, Feature 2: Physical-Waist_Circumference, Correlation: 0.85
- Feature 1: Physical-BMI, Feature 2: BIA-BIA_BMI, Correlation: 0.92
- Feature 1: Physical-Height, Feature 2: Physical-Weight, Correlation: 0.92
- Feature 1: Physical-Weight, Feature 2: Physical-Waist_Circumference, Correlation: 0.86
- Feature 1: Physical-Waist_Circumference, Feature 2: BIA-BIA_BMI, Correlation: 0.86
- Feature 1: Physical-Waist_Circumference, Feature 2: BIA-BIA_Fat, Correlation: 0.85
- Feature 1: Fitness_Endurance-Max_Stage, Feature 2: Fitness_Endurance-Time_Mins, Correlation: 0.86
- Feature 1: FGC-FGC_GSND, Feature 2: FGC-FGC_GSD, Correlation: 0.81
- Feature 1: FGC-FGC_SRL, Feature 2: FGC-FGC_SRR, Correlation: 0.91
- Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_BMR, Correlation: 0.99

Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_DEE, Correlation: 0.99
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_ECW, Correlation: 0.99
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_FFM, Correlation: 0.99
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_Fat, Correlation: -1.00
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_ICW, Correlation: 0.99
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_LDM, Correlation: 1.00
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_LST, Correlation: 0.98
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_SMM, Correlation: 0.98
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_TBW, Correlation: 0.99
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_DEE, Correlation: 1.00
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_ECW, Correlation: 1.00
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_FFM, Correlation: 1.00
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_Fat, Correlation: -0.99
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_ICW, Correlation: 1.00
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_LDM, Correlation: 1.00
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_LST, Correlation: 0.99
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_SMM, Correlation: 0.99
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_TBW, Correlation: 1.00
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_ECW, Correlation: 0.99
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_FFM, Correlation: 1.00
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_Fat, Correlation: -0.98
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_ICW, Correlation: 1.00
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_LDM, Correlation: 0.99
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_LST, Correlation: 0.99
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_SMM, Correlation: 0.99
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_TBW, Correlation: 1.00
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_FFM, Correlation: 1.00
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_Fat, Correlation: -0.99
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_ICW, Correlation: 1.00
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_LDM, Correlation: 1.00
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_LST, Correlation: 0.99
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_SMM, Correlation: 0.99
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_TBW, Correlation: 1.00
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_Fat, Correlation: -0.99
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_ICW, Correlation: 1.00
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_LDM, Correlation: 1.00
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_LST, Correlation: 0.99
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_SMM, Correlation: 0.99
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_TBW, Correlation: 1.00
Feature 1: BIA-BIA_FFMI, Feature 2: BIA-BIA_FMI, Correlation: -0.86
Feature 1: BIA-BIA_Fat, Feature 2: BIA-BIA_ICW, Correlation: -0.98
Feature 1: BIA-BIA_Fat, Feature 2: BIA-BIA_LDM, Correlation: -0.99
Feature 1: BIA-BIA_Fat, Feature 2: BIA-BIA_LST, Correlation: -0.97
Feature 1: BIA-BIA_Fat, Feature 2: BIA-BIA_SMM, Correlation: -0.98
Feature 1: BIA-BIA_Fat, Feature 2: BIA-BIA_TBW, Correlation: -0.99
Feature 1: BIA-BIA_ICW, Feature 2: BIA-BIA_LDM, Correlation: 1.00
Feature 1: BIA-BIA_ICW, Feature 2: BIA-BIA_LST, Correlation: 1.00
Feature 1: BIA-BIA_ICW, Feature 2: BIA-BIA_SMM, Correlation: 1.00

```

Feature 1: BIA-BIA_ICW, Feature 2: BIA-BIA_TBW, Correlation: 1.00
Feature 1: BIA-BIA_LDM, Feature 2: BIA-BIA_LST, Correlation: 0.99
Feature 1: BIA-BIA_LDM, Feature 2: BIA-BIA_SMM, Correlation: 0.99
Feature 1: BIA-BIA_LDM, Feature 2: BIA-BIA_TBW, Correlation: 1.00
Feature 1: BIA-BIA_LST, Feature 2: BIA-BIA_SMM, Correlation: 1.00
Feature 1: BIA-BIA_LST, Feature 2: BIA-BIA_TBW, Correlation: 1.00
Feature 1: BIA-BIA_SMM, Feature 2: BIA-BIA_TBW, Correlation: 0.99
Feature 1: PCIAT-PCIAT_03, Feature 2: PCIAT-PCIAT_Total, Correlation: 0.82
Feature 1: PCIAT-PCIAT_05, Feature 2: PCIAT-PCIAT_Total, Correlation: 0.83
Feature 1: PCIAT-PCIAT_15, Feature 2: PCIAT-PCIAT_Total, Correlation: 0.82
Feature 1: PCIAT-PCIAT_16, Feature 2: PCIAT-PCIAT_18, Correlation: 0.84
Feature 1: PCIAT-PCIAT_17, Feature 2: PCIAT-PCIAT_Total, Correlation: 0.82
Feature 1: PCIAT-PCIAT_Total, Feature 2: sii, Correlation: 0.89
Feature 1: SDS-SDS_Total_Raw, Feature 2: SDS-SDS_Total_T, Correlation: 1.00

```

analyzing the spread and missingness of PCIAT-PCIAT_01 to PCIAT-PCIAT_20:

```
[9]: # Step 1: Analyze Spread and Missingness for PCIAT Features (Updated)
import pandas as pd

# Select only PCIAT-PCIAT columns for analysis (exclude PCIAT-Season)
pciat_columns = [col for col in train_df.columns if 'PCIAT-' in col and col != 'PCIAT-PCIAT_Total' and col != 'PCIAT-Season']

# Calculate missing value percentages for each PCIAT feature
pciat_missing_percentage = train_df[pciat_columns].isnull().mean() * 100
print("\nMissing Value Percentage for PCIAT Features:")
print(pciat_missing_percentage)

# Calculate summary statistics for each PCIAT feature
pciat_summary_stats = train_df[pciat_columns].describe().T
print("\nSummary Statistics for PCIAT Features:")
print(pciat_summary_stats)

# Identify columns with high missing values (above 50%)
high_missing_pciat_columns = pciat_missing_percentage[pciat_missing_percentage >= 50].index
print("\nPCIAT Columns with High Missing Values (Above 50%):")
print(high_missing_pciat_columns)

# Check for skewness and kurtosis to understand the spread (excluding non-numeric columns)
pciat_skewness = train_df[pciat_columns].skew()
pciat_kurtosis = train_df[pciat_columns].kurtosis()
print("\nSkewness of PCIAT Features:")
print(pciat_skewness)
print("\nKurtosis of PCIAT Features:")
print(pciat_kurtosis)
```

Missing Value Percentage for PCIAT Features:

```
PCIAT-PCIAT_01    3.443329
PCIAT-PCIAT_02    3.395505
PCIAT-PCIAT_03    3.538977
PCIAT-PCIAT_04    3.538977
PCIAT-PCIAT_05    3.491153
PCIAT-PCIAT_06    3.491153
PCIAT-PCIAT_07    3.491153
PCIAT-PCIAT_08    3.538977
PCIAT-PCIAT_09    3.538977
PCIAT-PCIAT_10    3.443329
PCIAT-PCIAT_11    3.347681
PCIAT-PCIAT_12    3.491153
PCIAT-PCIAT_13    3.586801
PCIAT-PCIAT_14    3.443329
PCIAT-PCIAT_15    3.538977
PCIAT-PCIAT_16    3.634625
PCIAT-PCIAT_17    3.682449
PCIAT-PCIAT_18    3.491153
PCIAT-PCIAT_19    3.491153
PCIAT-PCIAT_20    3.395505
dtype: float64
```

Summary Statistics for PCIAT Features:

	count	mean	std	min	25%	50%	75%	max
PCIAT-PCIAT_01	2019.0	2.368004	1.661607	0.0	1.0	2.0	4.0	5.0
PCIAT-PCIAT_02	2020.0	2.125743	1.679651	0.0	0.0	2.0	4.0	5.0
PCIAT-PCIAT_03	2017.0	2.365394	1.570705	0.0	1.0	2.0	4.0	5.0
PCIAT-PCIAT_04	2017.0	0.784333	1.141998	0.0	0.0	0.0	1.0	5.0
PCIAT-PCIAT_05	2018.0	2.276016	1.701768	0.0	1.0	2.0	4.0	5.0
PCIAT-PCIAT_06	2018.0	1.016353	1.234213	0.0	0.0	1.0	1.0	5.0
PCIAT-PCIAT_07	2018.0	0.543112	1.016168	0.0	0.0	0.0	1.0	5.0
PCIAT-PCIAT_08	2017.0	1.189886	1.300998	0.0	0.0	1.0	2.0	5.0
PCIAT-PCIAT_09	2017.0	1.001983	1.204734	0.0	0.0	1.0	2.0	5.0
PCIAT-PCIAT_10	2019.0	1.274889	1.300384	0.0	0.0	1.0	2.0	5.0
PCIAT-PCIAT_11	2021.0	1.633845	1.518703	0.0	0.0	1.0	3.0	5.0
PCIAT-PCIAT_12	2018.0	0.227453	0.492179	0.0	0.0	0.0	0.0	5.0
PCIAT-PCIAT_13	2016.0	1.314980	1.381729	0.0	0.0	1.0	2.0	5.0
PCIAT-PCIAT_14	2019.0	0.987618	1.257030	0.0	0.0	1.0	2.0	5.0
PCIAT-PCIAT_15	2017.0	1.452652	1.462787	0.0	0.0	1.0	2.0	5.0
PCIAT-PCIAT_16	2015.0	1.428784	1.454290	0.0	0.0	1.0	2.0	5.0
PCIAT-PCIAT_17	2014.0	1.583416	1.417281	0.0	0.0	1.0	2.0	5.0
PCIAT-PCIAT_18	2018.0	1.599108	1.505679	0.0	0.0	1.0	2.0	5.0
PCIAT-PCIAT_19	2018.0	1.112488	1.305468	0.0	0.0	1.0	2.0	5.0
PCIAT-PCIAT_20	2020.0	0.913861	1.160906	0.0	0.0	1.0	1.0	5.0

PCIAT Columns with High Missing Values (Above 50%):

```
Index([], dtype='object')
```

```
Skewness of PCIAT Features:
```

PCIAT-PCIAT_01	0.018089
PCIAT-PCIAT_02	0.185529
PCIAT-PCIAT_03	-0.044011
PCIAT-PCIAT_04	1.693028
PCIAT-PCIAT_05	0.131485
PCIAT-PCIAT_06	1.410195
PCIAT-PCIAT_07	2.355935
PCIAT-PCIAT_08	1.041128
PCIAT-PCIAT_09	1.444419
PCIAT-PCIAT_10	0.895301
PCIAT-PCIAT_11	0.521314
PCIAT-PCIAT_12	2.846544
PCIAT-PCIAT_13	0.937216
PCIAT-PCIAT_14	1.340420
PCIAT-PCIAT_15	0.769705
PCIAT-PCIAT_16	0.893260
PCIAT-PCIAT_17	0.597016
PCIAT-PCIAT_18	0.745325
PCIAT-PCIAT_19	1.266126
PCIAT-PCIAT_20	1.550346

```
dtype: float64
```

```
Kurtosis of PCIAT Features:
```

PCIAT-PCIAT_01	-1.185968
PCIAT-PCIAT_02	-1.181542
PCIAT-PCIAT_03	-1.030276
PCIAT-PCIAT_04	2.529177
PCIAT-PCIAT_05	-1.191626
PCIAT-PCIAT_06	1.553860
PCIAT-PCIAT_07	5.650708
PCIAT-PCIAT_08	0.338986
PCIAT-PCIAT_09	1.871533
PCIAT-PCIAT_10	0.091892
PCIAT-PCIAT_11	-0.861567
PCIAT-PCIAT_12	13.212843
PCIAT-PCIAT_13	0.060331
PCIAT-PCIAT_14	1.172628
PCIAT-PCIAT_15	-0.382460
PCIAT-PCIAT_16	-0.114011
PCIAT-PCIAT_17	-0.518220
PCIAT-PCIAT_18	-0.387139
PCIAT-PCIAT_19	0.977074
PCIAT-PCIAT_20	2.205397

```
dtype: float64
```

```
[10]: train_df['PCIAT-PCIAT_Total'].value_counts()
```

```
[10]: PCIAT-PCIAT_Total
0.0      233
20.0      51
30.0      50
31.0      49
27.0      46
...
78.0      2
82.0      1
76.0      1
79.0      1
91.0      1
Name: count, Length: 89, dtype: int64
```

Implementation of GMM for Predicting PCIAT-PCIAT_Total:

```
[11]: # Generate interaction and polynomial terms for PCIAT columns
from itertools import combinations
from sklearn.preprocessing import PolynomialFeatures

# Create interaction terms
interaction_cols = ['PCIAT-PCIAT_01', 'PCIAT-PCIAT_02', 'PCIAT-PCIAT_05', ..., 'PCIAT-PCIAT_11']
interaction_data = pd.DataFrame(index=train_df.index)

# Generate interaction terms
for col1, col2 in combinations(interaction_cols, 2):
    interaction_data[f'{col1}_x_{col2}'] = train_df[col1] * train_df[col2]

# Generate polynomial features
poly = PolynomialFeatures(degree=2, include_bias=False)
poly_data = pd.DataFrame(poly.fit_transform(train_df[interaction_cols]).fillna(0))
poly_data.columns = poly.get_feature_names_out(interaction_cols)

# Combine interaction and polynomial features with existing data
train_df = pd.concat([train_df, interaction_data, poly_data], axis=1)
```

```
[12]: train_df.head()
```

```
[12]:      id Basic_Demos-Enroll_Season  Basic_Demos-Age  Basic_Demos-Sex \
0  00008ff9                  Fall          5.0          0.0
2  00105258                 Summer         10.0          1.0
3  00115b9f                 Winter          9.0          0.0
5  001f3379                 Spring         13.0          1.0
11 00abe655                 Fall          11.0          0.0
```

```

CGAS-Season CGAS-CGAS_Score Physical-Season Physical-BMI \
0 Winter 51.0 Fall 16.877316
2 Fall 71.0 Fall 16.648696
3 Fall 71.0 Summer 18.292347
5 Winter 50.0 Summer 22.279952
11 Summer 66.0 NaN NaN

Physical-Height Physical-Weight ... PCIAT-PCIAT_01^2 \
0 46.0 50.8 ... 25.0
2 56.5 75.6 ... 16.0
3 56.0 81.6 ... 9.0
5 59.5 112.2 ... 0.0
11 NaN NaN ... 9.0

PCIAT-PCIAT_01 PCIAT-PCIAT_02 PCIAT-PCIAT_01 PCIAT-PCIAT_05 \
0 20.0 20.0
2 8.0 20.0
3 9.0 6.0
5 0.0 0.0
11 9.0 3.0

PCIAT-PCIAT_01 PCIAT-PCIAT_11 PCIAT-PCIAT_02^2 \
0 20.0 16.0
2 12.0 4.0
3 0.0 9.0
5 0.0 0.0
11 0.0 9.0

PCIAT-PCIAT_02 PCIAT-PCIAT_05 PCIAT-PCIAT_02 PCIAT-PCIAT_11 \
0 16.0 16.0
2 10.0 6.0
3 6.0 0.0
5 0.0 0.0
11 3.0 0.0

PCIAT-PCIAT_05^2 PCIAT-PCIAT_05 PCIAT-PCIAT_11 PCIAT-PCIAT_11^2
0 16.0 16.0 16.0
2 25.0 15.0 9.0
3 4.0 0.0 0.0
5 0.0 0.0 0.0
11 1.0 0.0 0.0

```

[5 rows x 103 columns]

extracting the PCIAT-related columns and then applying standard scaling using StandardScaler. This step ensures that all the PCIAT features are on the same scale, which is crucial for clustering methods like Gaussian Mixture Models (GMM).

```
[13]: # Step 1: Define and Standardize PCIAT Columns Before Clustering
# Ensure the variable `scaled_pciat_data` is created using the following lines

from sklearn.preprocessing import StandardScaler

# Extract PCIAT-related columns (excluding non-numeric ones)
pciati_columns = [col for col in train_df.columns if 'PCIAT-' in col and col != 'PCIAT-PCIAT_Total' and col != 'PCIAT-Season']
pciati_data = train_df[pciati_columns]

# Apply Standard Scaling to the PCIAT columns
scaler = StandardScaler()
scaled_pciati_data = scaler.fit_transform(pciati_data)

# Now, proceed with your clustering and analysis steps
```

pciati_columns is a list of all columns containing “PCIAT-”, excluding PCIAT-PCIAT_Total (target column) and PCIAT-Season (non-numeric).

scaled_pciati_data stores the standardized values, which means each column will have a mean of 0 and a standard deviation of 1. This is essential to ensure that no single feature dominates the clustering process due to differences in scale.

helper functions for initializing GMM parameters and implementing the Expectation-Maximization (EM) algorithm to handle missing data.

Initialization (initialize_gmm_params):

Randomly initializes the means, covariances, and weights for the specified number of components (n_components).

E-Step (e_step):

Calculates the responsibility matrix, which represents the probability of each sample belonging to each Gaussian component. The function extracts non-missing values from each sample to handle the missing data scenario.

M-Step (m_step):

Updates the means, covariances, and weights of each component using the responsibilities computed during the E-step.

```
[14]: import numpy as np
import pandas as pd
from scipy.stats import multivariate_normal

# Step 1: Extract PCIAT columns and prepare data for GMM with missing values
pciati_columns = [col for col in train_df.columns if 'PCIAT-' in col and col != 'PCIAT-PCIAT_Total' and col != 'PCIAT-Season']
pciati_data = train_df[pciati_columns].values
```

```

# Step 2: Apply Standard Scaling
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaled_pciat_data = scaler.fit_transform(pciat_data)

# Step 3: Define helper functions for GMM with missing data (E-step, M-step, initialization)
def initialize_gmm_params(X, n_components, random_state=42):
    np.random.seed(random_state)
    n_features = X.shape[1]
    means = np.random.rand(n_components, n_features)
    covariances = np.array([np.identity(n_features) for _ in range(n_components)])
    weights = np.full(n_components, 1/n_components)
    return means, covariances, weights

# Updated e_step function with zero-size array and singular matrix handling
def e_step(X, means, covariances, weights, epsilon=1e-6):
    """
    Perform the E-step of the EM algorithm to calculate responsibilities.
    Handles cases where missing data leads to zero-size arrays or singular matrices.
    X: Data with missing values (NaNs).
    means: Array of shape (n_components, n_features).
    covariances: Array of shape (n_components, n_features, n_features).
    weights: Array of shape (n_components,).
    epsilon: Small value to add to diagonal of covariance matrix for numerical stability.
    """
    n_samples, n_features = X.shape
    n_components = means.shape[0]

    # Initialize responsibility matrix
    responsibilities = np.zeros((n_samples, n_components))

    for i in range(n_samples):
        for k in range(n_components):
            # Extract only non-missing dimensions for sample i and component k
            non_missing_idx = ~np.isnan(X[i, :])
            x_non_missing = X[i, non_missing_idx]
            mean_non_missing = means[k, non_missing_idx]

            # If no non-missing values are present, skip this component
            if x_non_missing.size == 0:
                responsibilities[i, k] = 0
                continue

```

```

# Subset the covariance matrix to include only non-missing features
cov_non_missing = covariances[k][np.ix_(non_missing_idx, □
non_missing_idx)]]

# Add epsilon to the diagonal to handle potential singular matrices
cov_non_missing += epsilon * np.eye(cov_non_missing.shape[0])

# Calculate the multivariate normal probability for non-missing data
try:
    responsibilities[i, k] = weights[k] * multivariate_normal.
pdf(x_non_missing, mean_non_missing, cov_non_missing)
except (LinAlgError, ValueError) as e:
    print(f"Error encountered for sample {i} and component {k}:□
{e}")
    responsibilities[i, k] = 0 # Set responsibility to 0 in case
of an error

# Normalize responsibilities for sample i if the sum is not zero
total_responsibility = np.sum(responsibilities[i, :])
if total_responsibility > 0:
    responsibilities[i, :] /= total_responsibility
else:
    # If no responsibilities are assigned (e.g., due to errors), assign
equal responsibility
    responsibilities[i, :] = 1.0 / n_components

return responsibilities

def m_step(X, responsibilities):
#     n_samples, n_features = X.shape
#     n_components = responsibilities.shape[1]
#     effective_samples = responsibilities.sum(axis=0)
#     weights = effective_samples / n_samples
#     means = np.zeros((n_components, n_features))
#     covariances = np.zeros((n_components, n_features, n_features))
#     for k in range(n_components):
#         for i in range(n_samples):
#             non_missing_idx = ~np.isnan(X[i, :])
#             means[k, non_missing_idx] += responsibilities[i, k] * X[i, □
non_missing_idx]
#             means[k] /= effective_samples[k]
#             for i in range(n_samples):
#                 non_missing_idx = ~np.isnan(X[i, :])
#                 x_centered = (X[i, non_missing_idx] - means[k, non_missing_idx]).
reshape(-1, 1)

```

```

# covariances[k][np.ix_(non_missing_idx, non_missing_idx)] += ↵
# responsibilities[i, k] * np.dot(x_centered, x_centered.T)
# covariances[k] /= effective_samples[k]
# return means, covariances, weights

# Modified M-step with covariance regularization
def m_step(X, responsibilities, reg_value=1e-5):
    n_samples, n_features = X.shape
    n_components = responsibilities.shape[1]
    effective_samples = responsibilities.sum(axis=0)
    weights = effective_samples / n_samples
    means = np.zeros((n_components, n_features))
    covariances = np.zeros((n_components, n_features, n_features))
    for k in range(n_components):
        for i in range(n_samples):
            non_missing_idx = ~np.isnan(X[i, :])
            means[k, non_missing_idx] += responsibilities[i, k] * X[i, ↵
            ↵non_missing_idx]
        means[k] /= effective_samples[k]
        for i in range(n_samples):
            non_missing_idx = ~np.isnan(X[i, :])
            x_centered = (X[i, non_missing_idx] - means[k, non_missing_idx]). ↵
            ↵reshape(-1, 1)
            covariances[k][np.ix_(non_missing_idx, non_missing_idx)] += ↵
            ↵responsibilities[i, k] * np.dot(x_centered, x_centered.T)
        covariances[k] /= effective_samples[k]
        covariances[k] += np.eye(n_features) * reg_value # Add regularization
    return means, covariances, weights

```

Initialization: Randomly initializes means, identity matrices for covariances, and equal weights.

E-Step: For each sample and each component, only non-missing features are used to calculate the probability density. Regularization (epsilon) is added to the covariance matrices to ensure numerical stability.

M-Step: Updates the parameters based on the responsibilities calculated in the E-step.

function gmm_with_missing_data iteratively performs the E-step and M-step until convergence, determined by the change in log-likelihood falling below a specified tolerance (tol).

```
[15]: # Step 4: Implement GMM with Missing Data
def gmm_with_missing_data(X, n_components=4, max_iter=100, tol=1e-4, ↵
    ↵random_state=42):
    means, covariances, weights = initialize_gmm_params(X, n_components, ↵
    ↵random_state)
    prev_log_likelihood = -np.inf
    for iteration in range(max_iter):
        responsibilities = e_step(X, means, covariances, weights)
        means, covariances, weights = m_step(X, responsibilities)
```

```

    log_likelihood = np.sum(np.log(np.sum(responsibilities, axis=1)))
    if np.abs(log_likelihood - prev_log_likelihood) < tol:
        print(f"Converged at iteration {iteration} for {n_components} components")
        break
    prev_log_likelihood = log_likelihood
return means, covariances, weights, responsibilities, log_likelihood

```

Performs the EM algorithm using e_step and m_step in a loop until convergence. The convergence is determined when the difference in log-likelihood between iterations is less than tol.

Returns the final means, covariances, responsibilities, and the final log_likelihood.

experiment_cluster_sizes is used to test the EM algorithm with varying numbers of clusters to identify the best number of components for GMM based on log-likelihood.

```
[16]: # Step 5: Experiment with Different Cluster Sizes
def experiment_cluster_sizes(X, cluster_sizes=[2, 3, 4, 5, 6], max_iter=100, tol=1e-4, random_state=42):
    log_likelihoods = []
    best_gmm_params = {}
    for n_components in cluster_sizes:
        print(f"Testing with {n_components} clusters...")
        means, covariances, weights, responsibilities, log_likelihood = gmm_with_missing_data(
            X, n_components=n_components, max_iter=max_iter, tol=tol, random_state=random_state)
        log_likelihoods.append(log_likelihood)
        best_gmm_params[n_components] = (means, covariances, weights, responsibilities)
    return log_likelihoods, best_gmm_params
```

```
# Step 6: Run the Cluster Size Experimentation
# Experiment with more clusters
cluster_sizes = [6, 7, 8, 9, 10] # Extended cluster sizes
log_likelihoods, gmm_params_by_cluster = experiment_cluster_sizes(scaled_pciat_data, cluster_sizes)
```

```
# Select the best model based on log-likelihood
best_n_components = cluster_sizes[np.argmax(log_likelihoods)]
best_means, best_covariances, best_weights, best_responsibilities = gmm_params_by_cluster[best_n_components]
```

```
Testing with 6 clusters...
Converged at iteration 1 for 6 components.
Testing with 7 clusters...
Converged at iteration 1 for 7 components.
Testing with 8 clusters...
Converged at iteration 1 for 8 components.
```

```

Testing with 9 clusters..
Converged at iteration 1 for 9 components.
Testing with 10 clusters..
Converged at iteration 1 for 10 components.

```

Tests cluster sizes ranging from 2 to 6.

For each cluster size, gmm_with_missing_data is called, and the log-likelihood values are stored to identify the best-performing model.

After identifying the best cluster size, the code fills the missing PCIAT-PCIAT_Total values based on the derived clusters.

```

[17]: # Step 4: Plot Log-Likelihoods for Different Cluster Sizes
plt.figure(figsize=(10, 6))
plt.plot(cluster_sizes, log_likelihoods, marker='o', linestyle='--', color='b')
plt.title("Log-Likelihoods for Different Cluster Sizes")
plt.xlabel("Number of Clusters")
plt.ylabel("Log-Likelihood")
plt.grid(True)
plt.show()

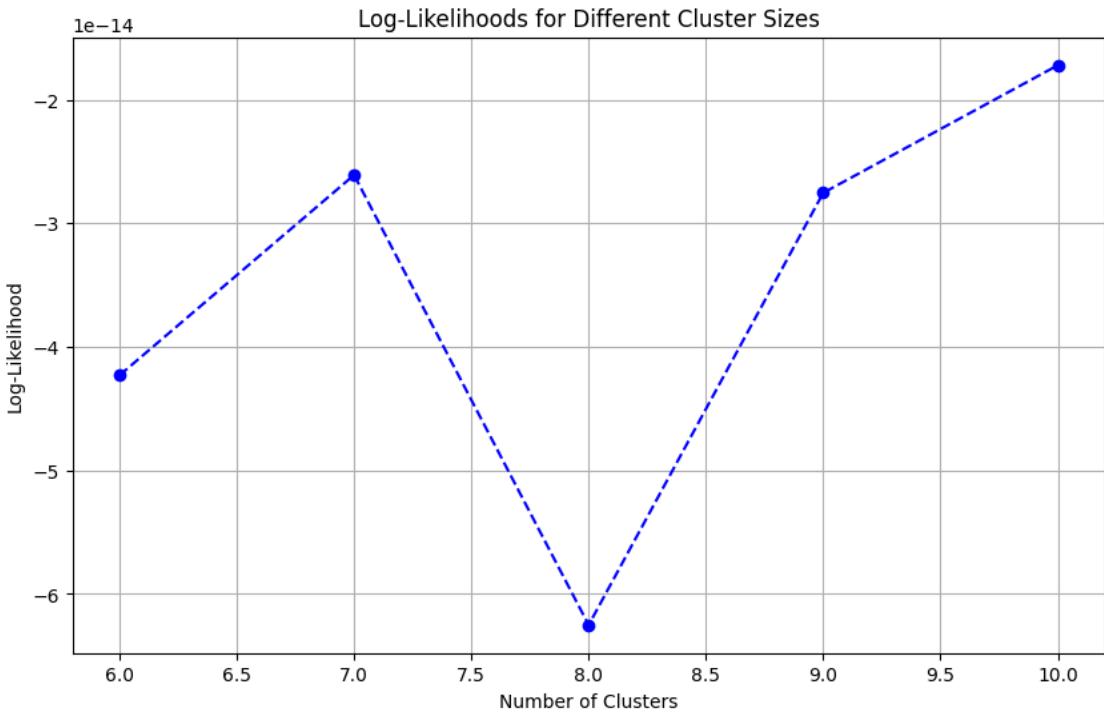
# Step 5: Select the Best Model Based on Log-Likelihood
best_n_components = cluster_sizes[np.argmax(log_likelihoods)]
best_means, best_covariances, best_weights, best_responsibilities =
    ↪gmm_params_by_cluster[best_n_components]
print(f"\nSelected {best_n_components} clusters as the best model based on
    ↪log-likelihood.")

# Step 6: Derive Missing PCIAT-PCIAT_Total Values Using Best GMM Parameters
# Calculate the mean PCIAT-PCIAT_Total for each cluster using non-missing values
train_df['PCIAT_Cluster'] = np.argmax(best_responsibilities, axis=1) # Assign
    ↪clusters
cluster_means = train_df.groupby('PCIAT_Cluster')['PCIAT-PCIAT_Total'].mean()

# Fill missing PCIAT-PCIAT_Total values based on cluster-specific mean
train_df['PCIAT-PCIAT_Total'] = train_df.apply(
    lambda row: cluster_means[row['PCIAT_Cluster']] if np.
        ↪isnan(row['PCIAT-PCIAT_Total']) else row['PCIAT-PCIAT_Total'], axis=1
)

# Step 7: Validation - Calculate RMSE and MSE
# Get original non-missing and imputed values for comparison
original_pciat_total = train_df[~train_df['PCIAT-PCIAT_Total'].
    ↪isnull()]['PCIAT-PCIAT_Total']
imputed_pciat_total = train_df[~train_df['PCIAT-PCIAT_Total'].isnull()].
    ↪groupby('PCIAT_Cluster')['PCIAT-PCIAT_Total'].transform('mean')

```



Selected 10 clusters as the best model based on log-likelihood.

The code assigns clusters to each sample based on the maximum responsibility.

The mean PCIAT-PCIAT_Total value for each cluster is used to fill in the missing values, ensuring the filled values reflect the cluster's characteristics.

code calculates the Root Mean Squared Error (RMSE) and Mean Squared Error (MSE) between the original PCIAT-PCIAT_Total values and the cluster-derived values to validate the imputation.

```
[18]: # Calculate RMSE and MSE
from sklearn.metrics import mean_squared_error
rmse = np.sqrt(mean_squared_error(original_pciat_total, imputed_pciat_total))
mse = mean_squared_error(original_pciat_total, imputed_pciat_total)

print(f"\nValidation Results for PCIAT-PCIAT_Total Imputation:")
print(f"RMSE: {rmse:.4f}")
print(f"MSE: {mse:.4f}")
```

Validation Results for PCIAT-PCIAT_Total Imputation:

RMSE: 9.9423

MSE: 98.8499

RMSE: Measures the standard deviation of the residuals (prediction errors). A lower RMSE indicates better accuracy.

MSE: Measures the average squared difference between the observed and predicted values. A lower MSE indicates better fit.

```
[19]: pd.set_option('display.max_columns', None)
train_df.head()
```

	id	Basic_Demos-Enroll_Season	Basic_Demos-Age	Basic_Demos-Sex	\
0	00008ff9	Fall	5.0	0.0	
2	00105258	Summer	10.0	1.0	
3	00115b9f	Winter	9.0	0.0	
5	001f3379	Spring	13.0	1.0	
11	00abe655	Fall	11.0	0.0	

	CGAS-Season	CGAS-CGAS_Score	Physical-Season	Physical-BMI	\
0	Winter	51.0	Fall	16.877316	
2	Fall	71.0	Fall	16.648696	
3	Fall	71.0	Summer	18.292347	
5	Winter	50.0	Summer	22.279952	
11	Summer	66.0	NaN	NaN	

	Physical-Height	Physical-Weight	Physical-Waist_Circumference	\
0	46.0	50.8	NaN	
2	56.5	75.6	NaN	
3	56.0	81.6	NaN	
5	59.5	112.2	NaN	
11	NaN	NaN	NaN	

	Physical-Diastolic_BP	Physical-HeartRate	Physical-Systolic_BP	\
0	NaN	NaN	NaN	
2	65.0	94.0	117.0	
3	60.0	97.0	117.0	
5	60.0	73.0	102.0	
11	NaN	NaN	NaN	

	Fitness_Endurance-Season	Fitness_Endurance-Max_Stage	\
0	NaN	NaN	
2	Fall	5.0	
3	Summer	6.0	
5	NaN	NaN	
11	NaN	NaN	

	Fitness_Endurance-Time_Mins	Fitness_Endurance-Time_Sec	FGC-Season	\
0	NaN	NaN	Fall	
2	7.0	33.0	Fall	
3	9.0	37.0	Summer	
5	NaN	NaN	Summer	
11	NaN	NaN	Winter	

	FGC-FGC_CU	FGC-FGC_CU_Zone	FGC-FGC_GSND	FGC-FGC_GSND_Zone	FGC-FGC_GSD	\
0	0.0	0.0	NaN	NaN	NaN	
2	20.0	1.0	10.2	1.0	14.7	
3	18.0	1.0	NaN	NaN	NaN	
5	12.0	0.0	16.5	2.0	17.9	
11	NaN	NaN	NaN	NaN	NaN	
	FGC-FGC_GSD_Zone	FGC-FGC_PU	FGC-FGC_PU_Zone	FGC-FGC_SRL	FGC-FGC_SRL_Zone	\
0	NaN	0.0	0.0	7.0	0.0	
2	2.0	7.0	1.0	10.0	7.0	
3	NaN	5.0	0.0	7.0	5.0	
5	2.0	6.0	0.0	10.0	6.0	
11	NaN	NaN	NaN	NaN	NaN	
	FGC-FGC_SRL_Zone	FGC-FGC_SRR	FGC-FGC_SRR_Zone	FGC-FGC_TL	FGC-FGC_TL_Zone	\
0	0.0	6.0	0.0	6.0	0.0	
2	1.0	10.0	1.0	5.0	1.0	
3	0.0	7.0	0.0	7.0	7.0	
5	1.0	11.0	1.0	8.0	11.0	
11	NaN	NaN	NaN	NaN	NaN	
	FGC-FGC_TL_Zone	BIA-Season	BIA-BIA_Activity_Level_num	BIA-BIA_BMC	BIA-BIA_BMC_Zone	\
0	1.0	Fall	2.0	2.66855	2.0	
2	0.0	NaN	NaN	NaN	NaN	
3	1.0	Summer	3.0	3.84191	3.0	
5	0.0	Summer	2.0	4.33036	2.0	
11	NaN	NaN	NaN	NaN	NaN	
	BIA-BIA_BMI	BIA-BIA_BMR	BIA-BIA_DEE	BIA-BIA_ECW	BIA-BIA_FFM	\
0	16.8792	932.498	1492.00	8.25598	41.5862	
2	NaN	NaN	NaN	NaN	NaN	
3	18.2943	1131.430	1923.44	15.59250	62.7757	
5	30.1865	1330.970	1996.45	30.21240	84.0285	
11	NaN	NaN	NaN	NaN	NaN	
	BIA-BIA_FFMI	BIA-BIA_FMI	BIA-BIA_Fat	BIA-BIA_Frame_num	BIA-BIA_ICW	\
0	13.8177	3.06143	9.21377	1.0	24.4349	
2	NaN	NaN	NaN	NaN	NaN	
3	14.0740	4.22033	18.82430	2.0	30.4041	
5	16.6877	13.49880	67.97150	2.0	32.9141	
11	NaN	NaN	NaN	NaN	NaN	
	BIA-BIA_LDM	BIA-BIA_LST	BIA-BIA_SMM	BIA-BIA_TBW	PAQ_A-Season	\
0	8.89536	38.9177	19.5413	32.6909	NaN	
2	NaN	NaN	NaN	NaN	NaN	
3	16.77900	58.9338	26.4798	45.9966	NaN	

5	20.90200	79.6982	35.3804	63.1265	NaN
11	NaN	NaN	NaN	NaN	NaN
	PAQ_A-PAQ_A_Total	PAQ_C-Season	PAQ_C-PAQ_C_Total	PCIAT-Season	\
0	NaN	NaN	NaN	Fall	
2	NaN	Summer	2.170	Fall	
3	NaN	Winter	2.451	Summer	
5	NaN	Spring	4.110	Summer	
11	NaN	Winter	1.100	Winter	
	PCIAT-PCIAT_01	PCIAT-PCIAT_02	PCIAT-PCIAT_03	PCIAT-PCIAT_04	\
0	5.0	4.0	4.0	0.0	
2	5.0	2.0	2.0	1.0	
3	4.0	2.0	4.0	0.0	
5	3.0	3.0	3.0	0.0	
11	2.0	2.0	1.0	0.0	
	PCIAT-PCIAT_05	PCIAT-PCIAT_06	PCIAT-PCIAT_07	PCIAT-PCIAT_08	\
0	4.0	0.0	0.0	4.0	
2	2.0	1.0	1.0	2.0	
3	5.0	1.0	0.0	3.0	
5	2.0	1.0	0.0	2.0	
11	3.0	0.0	0.0	0.0	
	PCIAT-PCIAT_09	PCIAT-PCIAT_10	PCIAT-PCIAT_11	PCIAT-PCIAT_12	\
0	0.0	0.0	4.0	0.0	
2	1.0	1.0	1.0	0.0	
3	2.0	2.0	3.0	0.0	
5	2.0	1.0	0.0	1.0	
11	0.0	0.0	0.0	0.0	
	PCIAT-PCIAT_13	PCIAT-PCIAT_14	PCIAT-PCIAT_15	PCIAT-PCIAT_16	\
0	4.0	4.0	4.0	4.0	
2	1.0	1.0	1.0	0.0	
3	3.0	0.0	0.0	3.0	
5	3.0	3.0	2.0	1.0	
11	0.0	0.0	0.0	0.0	
	PCIAT-PCIAT_17	PCIAT-PCIAT_18	PCIAT-PCIAT_19	PCIAT-PCIAT_20	\
0	4.0	4.0	2.0	4.0	
2	2.0	2.0	1.0	1.0	
3	4.0	3.0	4.0	1.0	
5	3.0	1.0	2.0	1.0	
11	1.0	0.0	1.0	0.0	
	PCIAT-PCIAT_Total	SDS-Season	SDS-SDS_Total_Raw	SDS-SDS_Total_T	\
0	55.0	NaN	NaN	NaN	

2	28.0	Fall	38.0	54.0	
3	44.0	Summer	31.0	45.0	
5	34.0	Summer	40.0	56.0	
11	10.0	Winter	42.0	59.0	
0	PreInt_EduHx-Season	PreInt_EduHx-computerinternet_hoursday	sii	Age_Group	\
0	Fall		3.0	2.0	NaN
2	Summer		2.0	0.0	5-10
3	Winter		0.0	1.0	5-10
5	Spring		0.0	1.0	11-15
11	Fall		0.0	0.0	11-15
0	PCIAT-PCIAT_01_x_PCIAT-PCIAT_02	PCIAT-PCIAT_01_x_PCIAT-PCIAT_05			\
0		20.0		20.0	
2		10.0		10.0	
3		8.0		20.0	
5		9.0		6.0	
11		4.0		6.0	
0	PCIAT-PCIAT_01_x_PCIAT-PCIAT_11	PCIAT-PCIAT_02_x_PCIAT-PCIAT_05			\
0		20.0		16.0	
2		5.0		4.0	
3		12.0		10.0	
5		0.0		6.0	
11		0.0		6.0	
0	PCIAT-PCIAT_02_x_PCIAT-PCIAT_11	PCIAT-PCIAT_05_x_PCIAT-PCIAT_11			\
0		16.0		16.0	
2		2.0		2.0	
3		6.0		15.0	
5		0.0		0.0	
11		0.0		0.0	
0	PCIAT-PCIAT_01	PCIAT-PCIAT_02	PCIAT-PCIAT_05	PCIAT-PCIAT_11	\
0	5.0	4.0	4.0	4.0	
2	4.0	2.0	5.0	3.0	
3	3.0	3.0	2.0	0.0	
5	0.0	0.0	0.0	0.0	
11	3.0	3.0	1.0	0.0	
0	PCIAT-PCIAT_01^2	PCIAT-PCIAT_01	PCIAT-PCIAT_02		\
0		25.0	20.0		
2		16.0	8.0		
3		9.0	9.0		
5		0.0	0.0		
11		9.0	9.0		

```

PCIAT-PCIAT_01 PCIAT-PCIAT_05 PCIAT-PCIAT_01 PCIAT-PCIAT_11 \
0 20.0 20.0
2 20.0 12.0
3 6.0 0.0
5 0.0 0.0
11 3.0 0.0

PCIAT-PCIAT_02^2 PCIAT-PCIAT_02 PCIAT-PCIAT_05 \
0 16.0 16.0
2 4.0 10.0
3 9.0 6.0
5 0.0 0.0
11 9.0 3.0

PCIAT-PCIAT_02 PCIAT-PCIAT_11 PCIAT-PCIAT_05^2 \
0 16.0 16.0
2 6.0 25.0
3 0.0 4.0
5 0.0 0.0
11 0.0 1.0

PCIAT-PCIAT_05 PCIAT-PCIAT_11 PCIAT-PCIAT_11^2 PCIAT_Cluster
0 16.0 16.0 5
2 15.0 9.0 7
3 0.0 0.0 4
5 0.0 0.0 3
11 0.0 0.0 3

```

[20]: `train_df['PCIAT-PCIAT_Total'].value_counts()`

[20]: PCIAT-PCIAT_Total

20.814159	435
0.000000	233
8.770492	186
50.897436	108
20.627907	82
...	
78.000000	2
82.000000	1
76.000000	1
79.000000	1
91.000000	1

Name: count, Length: 99, dtype: int64

[21]: `# Step: Remove PCIAT sub-columns and clustering-specific features`
`# Remove PCIAT-related columns and clustering features`

```

columns_to_remove = [col for col in train_df.columns if 'PCIAT-' in col and col
                     != 'PCIAT-PCIAT_Total']
train_df.drop(columns=columns_to_remove, inplace=True)

train_df.head()

```

```
[21]:      id Basic_Demos-Enroll_Season  Basic_Demos-Age  Basic_Demos-Sex \
0    00008ff9                      Fall             5.0            0.0
2    00105258                      Summer           10.0            1.0
3    00115b9f                      Winter            9.0            0.0
5    001f3379                      Spring           13.0            1.0
11   00abe655                      Fall             11.0            0.0

      CGAS-Season  CGAS-CGAS_Score  Physical-Season  Physical-BMI \
0        Winter          51.0          Fall       16.877316
2        Fall           71.0          Fall       16.648696
3        Fall           71.0         Summer      18.292347
5        Winter          50.0         Summer      22.279952
11       Summer          66.0           NaN           NaN

      Physical-Height  Physical-Weight  Physical-Waist_Circumference \
0              46.0          50.8                  NaN
2              56.5          75.6                  NaN
3              56.0          81.6                  NaN
5              59.5         112.2                  NaN
11             NaN           NaN                  NaN

      Physical-Diastolic_BP  Physical-HeartRate  Physical-Systolic_BP \
0                  NaN                  NaN                  NaN
2                 65.0                 94.0                117.0
3                 60.0                 97.0                117.0
5                 60.0                 73.0                102.0
11                NaN                  NaN                  NaN

      Fitness_Endurance-Season  Fitness_Endurance-Max_Stage \
0                  NaN                  NaN
2                  Fall                  5.0
3                  Summer                6.0
5                  NaN                  NaN
11                 NaN                  NaN

      Fitness_Endurance-Time_Mins  Fitness_Endurance-Time_Sec  FGC-Season \
0                  NaN                  NaN            Fall
2                  7.0                  33.0            Fall
3                  9.0                  37.0        Summer
5                  NaN                  NaN        Summer
11                 NaN                  NaN        Winter

```

	FGC-FGC_CU	FGC-FGC_CU_Zone	FGC-FGC_GSND	FGC-FGC_GSND_Zone	FGC-FGC_GSD	\
0	0.0	0.0	NaN	NaN	NaN	
2	20.0	1.0	10.2	1.0	14.7	
3	18.0	1.0	NaN	NaN	NaN	
5	12.0	0.0	16.5	2.0	17.9	
11	NaN	NaN	NaN	NaN	NaN	
	FGC-FGC_GSD_Zone	FGC-FGC_PU	FGC-FGC_PU_Zone	FGC-FGC_SRL	FGC-FGC_SRL_Zone	\
0	NaN	0.0	0.0	7.0	0.0	
2	2.0	7.0	1.0	10.0	2.0	
3	NaN	5.0	0.0	7.0	5.0	
5	2.0	6.0	0.0	10.0	2.0	
11	NaN	NaN	NaN	NaN	NaN	
	FGC-FGC_SRL_Zone	FGC-FGC_SRR	FGC-FGC_SRR_Zone	FGC-FGC_TL	FGC-FGC_TL_Zone	\
0	0.0	6.0	0.0	6.0	0.0	
2	1.0	10.0	1.0	5.0	1.0	
3	0.0	7.0	0.0	7.0	0.0	
5	1.0	11.0	1.0	8.0	1.0	
11	NaN	NaN	NaN	NaN	NaN	
	FGC-FGC_TL_Zone	BIA-Season	BIA-BIA_Activity_Level_num	BIA-BIA_BMC	BIA-BIA_BMC_Zone	\
0	1.0	Fall	2.0	2.66855	1.0	
2	0.0	NaN	NaN	NaN	0.0	
3	1.0	Summer	3.0	3.84191	1.0	
5	0.0	Summer	2.0	4.33036	0.0	
11	NaN	NaN	NaN	NaN	NaN	
	BIA-BIA_BMI	BIA-BIA_BMR	BIA-BIA_DEE	BIA-BIA_ECW	BIA-BIA_FFM	\
0	16.8792	932.498	1492.00	8.25598	41.5862	
2	NaN	NaN	NaN	NaN	NaN	
3	18.2943	1131.430	1923.44	15.59250	62.7757	
5	30.1865	1330.970	1996.45	30.21240	84.0285	
11	NaN	NaN	NaN	NaN	NaN	
	BIA-BIA_FFMI	BIA-BIA_FMI	BIA-BIA_Fat	BIA-BIA_Frame_num	BIA-BIA_ICW	\
0	13.8177	3.06143	9.21377	1.0	24.4349	
2	NaN	NaN	NaN	NaN	NaN	
3	14.0740	4.22033	18.82430	2.0	30.4041	
5	16.6877	13.49880	67.97150	2.0	32.9141	
11	NaN	NaN	NaN	NaN	NaN	
	BIA-BIA_LDM	BIA-BIA_LST	BIA-BIA_SMM	BIA-BIA_TBW	PAQ_A-Season	\
0	8.89536	38.9177	19.5413	32.6909	NaN	
2	NaN	NaN	NaN	NaN	NaN	
3	16.77900	58.9338	26.4798	45.9966	NaN	

5	20.90200	79.6982	35.3804	63.1265	NaN
11	NaN	NaN	NaN	NaN	NaN
	PAQ_A-PAQ_A_Total	PAQ_C-Season	PAQ_C-PAQ_C_Total	PCIAT-PCIAT_Total	\
0	NaN	NaN	NaN	55.0	
2	NaN	Summer	2.170	28.0	
3	NaN	Winter	2.451	44.0	
5	NaN	Spring	4.110	34.0	
11	NaN	Winter	1.100	10.0	
	SDS-Season	SDS-SDS_Total_Raw	SDS-SDS_Total_T	PreInt_EduHx-Season	\
0	NaN	NaN	NaN	Fall	
2	Fall	38.0	54.0	Summer	
3	Summer	31.0	45.0	Winter	
5	Summer	40.0	56.0	Spring	
11	Winter	42.0	59.0	Fall	
	PreInt_EduHx-computerinternet_hoursday	sii	Age_Group	PCIAT_Cluster	
0		3.0	2.0	NaN	5
2		2.0	0.0	5-10	7
3		0.0	1.0	5-10	4
5		0.0	1.0	11-15	3
11		0.0	0.0	11-15	3

Generate interaction terms based on key multimodal features to capture complex relationships.

Approach:

Identify Key Features: From the previous correlation analysis, we'll pick the top correlated features for interaction term creation.

Create Interaction Terms: For each pair of selected features, we'll generate interaction terms (e.g., feature1 * feature2).

Validate Interaction Terms: Ensure that these new features provide additional explanatory power without adding noise.

Implementation: Identify Key Multimodal Features:

Based on our previous correlation analysis, we'll focus on features from different modalities (e.g., cognitive and physical) that are highly correlated. Selected features for interaction terms: CGAS-CGAS_Score (Cognitive Score) with other cognitive features. Physical-BMI with other physical features like Physical-Height. Any other cross-modality interactions that might be valuable. Create Interaction Terms:

Generate pairwise interaction terms between selected features and append them to the dataset.
Validate and Log Interaction Terms:

Check the correlation of new interaction terms with existing features. Ensure no multicollinearity is introduced.

```
[22]: # Step 4.1: Create Interaction Terms

# List of key multimodal features for interaction term creation based on ↴
# previous correlation analysis
key_features = [
    'CGAS-CGAS_Score',
    'SDS-SDS_Total_Raw',
    'Physical-BMI',
    'Physical-Height',
    'PreInt_EduHx-computerinternet_hoursday'
]

# Create an empty dictionary to store interaction terms for documentation
interaction_terms = {}

# Create pairwise interaction terms between key multimodal features
for i in range(len(key_features)):
    for j in range(i+1, len(key_features)):
        feature_1 = key_features[i]
        feature_2 = key_features[j]

        # Create a new interaction term
        interaction_term_name = f"{feature_1}_x_{feature_2}"

        # Ensure both columns are numeric before creating the interaction term
        if pd.api.types.is_numeric_dtype(train_df[feature_1]) and pd.api.types.
            ↴is_numeric_dtype(train_df[feature_2]):
            train_df[interaction_term_name] = train_df[feature_1] * ↴
            ↴train_df[feature_2]

        # Store interaction term in dictionary for reference if successfully ↴
        # created
        if interaction_term_name in train_df.columns:
            interaction_terms[interaction_term_name] = (feature_1, feature_2)

# Log created interaction terms for verification
print(f"Interaction terms created: {list(interaction_terms.keys())}")

# Display the first few rows of the training data to verify
print("\nTraining Data with New Interaction Terms:")
train_df.head()
```

Interaction terms created: ['CGAS-CGAS_Score_x_SDS-SDS_Total_Raw', 'CGAS-CGAS_Score_x_Physical-BMI', 'CGAS-CGAS_Score_x_Physical-Height', 'CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet_hoursday', 'SDS-SDS_Total_Raw_x_Physical-BMI', 'SDS-SDS_Total_Raw_x_Physical-Height', 'SDS-SDS_Total_Raw_x_PreInt_EduHx-computerinternet_hoursday', 'Physical-

```
BMI_x_Physical-Height', 'Physical-BMI_x_PreInt_EduHx-computerinternet_hoursday',
'Physical-Height_x_PreInt_EduHx-computerinternet_hoursday']
```

Training Data with New Interaction Terms:

```
[22]:      id Basic_Demos-Enroll_Season  Basic_Demos-Age  Basic_Demos-Sex \
0    00008ff9                      Fall            5.0          0.0
2    00105258                      Summer          10.0         1.0
3    00115b9f                      Winter          9.0          0.0
5    001f3379                      Spring          13.0         1.0
11   00abe655                      Fall           11.0         0.0

      CGAS-Season  CGAS-CGAS_Score  Physical-Season  Physical-BMI \
0      Winter        51.0          Fall       16.877316
2      Fall          71.0          Fall       16.648696
3      Fall          71.0          Summer     18.292347
5      Winter        50.0          Summer     22.279952
11   Summer        66.0          NaN        NaN

      Physical-Height  Physical-Weight  Physical-Waist_Circumference \
0            46.0          50.8                  NaN
2            56.5          75.6                  NaN
3            56.0          81.6                  NaN
5            59.5         112.2                  NaN
11           NaN          NaN                  NaN

      Physical-Diastolic_BP  Physical-HeartRate  Physical-Systolic_BP \
0                  NaN                  NaN                  NaN
2            65.0          94.0          117.0
3            60.0          97.0          117.0
5            60.0          73.0          102.0
11           NaN          NaN                  NaN

      Fitness_Endurance-Season  Fitness_Endurance-Max_Stage \
0                  NaN                  NaN
2                  Fall             5.0
3                  Summer           6.0
5                  NaN              NaN
11                 NaN              NaN

      Fitness_Endurance-Time_Mins  Fitness_Endurance-Time_Sec FGC-Season \
0                  NaN                  NaN          Fall
2                  7.0                33.0          Fall
3                  9.0                37.0        Summer
5                  NaN                  NaN        Summer
11                 NaN                  NaN        Winter
```

	FGC-FGC CU	FGC-FGC CU_Zone	FGC-FGC GSND	FGC-FGC GSND_Zone	FGC-FGC GSD	\
0	0.0	0.0	NaN	NaN	NaN	
2	20.0	1.0	10.2	1.0	14.7	
3	18.0	1.0	NaN	NaN	NaN	
5	12.0	0.0	16.5	2.0	17.9	
11	NaN	NaN	NaN	NaN	NaN	
	FGC-FGC GSD_Zone	FGC-FGC PU	FGC-FGC PU_Zone	FGC-FGC SRL	\	
0	NaN	0.0	0.0	7.0		
2	2.0	7.0	1.0	10.0		
3	NaN	5.0	0.0	7.0		
5	2.0	6.0	0.0	10.0		
11	NaN	NaN	NaN	NaN		
	FGC-FGC SRL_Zone	FGC-FGC SRR	FGC-FGC SRR_Zone	FGC-FGC TL	\	
0	0.0	6.0	0.0	6.0		
2	1.0	10.0	1.0	5.0		
3	0.0	7.0	0.0	7.0		
5	1.0	11.0	1.0	8.0		
11	NaN	NaN	NaN	NaN		
	FGC-FGC TL_Zone	BIA-Season	BIA-BIA_Activity_Level_num	BIA-BIA_BMC	\	
0	1.0	Fall	2.0	2.66855		
2	0.0	NaN	NaN	NaN		
3	1.0	Summer	3.0	3.84191		
5	0.0	Summer	2.0	4.33036		
11	NaN	NaN	NaN	NaN		
	BIA-BIA BMI	BIA-BIA BMR	BIA-BIA DEE	BIA-BIA ECW	BIA-BIA FFM	\
0	16.8792	932.498	1492.00	8.25598	41.5862	
2	NaN	NaN	NaN	NaN	NaN	
3	18.2943	1131.430	1923.44	15.59250	62.7757	
5	30.1865	1330.970	1996.45	30.21240	84.0285	
11	NaN	NaN	NaN	NaN	NaN	
	BIA-BIA FFI	BIA-BIA FMI	BIA-BIA Fat	BIA-BIA Frame_num	BIA-BIA ICW	\
0	13.8177	3.06143	9.21377	1.0	24.4349	
2	NaN	NaN	NaN	NaN	NaN	
3	14.0740	4.22033	18.82430	2.0	30.4041	
5	16.6877	13.49880	67.97150	2.0	32.9141	
11	NaN	NaN	NaN	NaN	NaN	
	BIA-BIA LDM	BIA-BIA LST	BIA-BIA SMM	BIA-BIA TBW	PAQ_A-Season	\
0	8.89536	38.9177	19.5413	32.6909	NaN	
2	NaN	NaN	NaN	NaN	NaN	
3	16.77900	58.9338	26.4798	45.9966	NaN	
5	20.90200	79.6982	35.3804	63.1265	NaN	

11	NaN	NaN	NaN	NaN	NaN
	PAQ_A-PAQ_A_Total	PAQ_C-Season	PAQ_C-PAQ_C_Total	PCIAT-PCIAT_Total	\
0	NaN	NaN	NaN	55.0	
2	NaN	Summer	2.170	28.0	
3	NaN	Winter	2.451	44.0	
5	NaN	Spring	4.110	34.0	
11	NaN	Winter	1.100	10.0	
	SDS-Season	SDS-SDS_Total_Raw	SDS-SDS_Total_T	PreInt_EduHx-Season	\
0	NaN	NaN	NaN	Fall	
2	Fall	38.0	54.0	Summer	
3	Summer	31.0	45.0	Winter	
5	Summer	40.0	56.0	Spring	
11	Winter	42.0	59.0	Fall	
	PreInt_EduHx-computerinternet_hoursday	sii	Age_Group	PCIAT_Cluster	\
0		3.0	2.0	NaN	5
2		2.0	0.0	5-10	7
3		0.0	1.0	5-10	4
5		0.0	1.0	11-15	3
11		0.0	0.0	11-15	3
	CGAS-CGAS_Score_x_SDSDS_Total_Raw	CGAS-CGAS_Score_x_Physical-BMI			\
0		NaN	860.743100		
2		2698.0	1182.057420		
3		2201.0	1298.756633		
5		2000.0	1113.997599		
11		2772.0	NaN		
	CGAS-CGAS_Score_x_Physical-Height	\			
0		2346.0			
2		4011.5			
3		3976.0			
5		2975.0			
11		NaN			
	CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet_hoursday	\			
0		153.0			
2		142.0			
3		0.0			
5		0.0			
11		0.0			
	SDS-SDS_Total_Raw_x_Physical-BMI	SDS-SDS_Total_Raw_x_Physical-Height			\
0		NaN	NaN		
2		632.650450	2147.0		

```

3          567.062755          1736.0
5          891.198079          2380.0
11         NaN                  NaN

    SDS-SDS_Total_Raw_x_PreInt_EduHx-computerinternet_hoursday \
0                      NaN
2                      76.0
3                      0.0
5                      0.0
11                     0.0

    Physical-BMI_x_Physical-Height \
0          776.356522
2          940.651327
3          1024.371429
5          1325.657143
11         NaN

    Physical-BMI_x_PreInt_EduHx-computerinternet_hoursday \
0          50.631947
2          33.297392
3          0.000000
5          0.000000
11         NaN

    Physical-Height_x_PreInt_EduHx-computerinternet_hoursday
0          138.0
2          113.0
3          0.0
5          0.0
11         NaN

```

[23]: ID_arr = train_df['id']

[24]: # Step 2: Compute the correlation matrix for original and interaction terms
Filter only numeric columns
numeric_cols_with_interactions = train_df.select_dtypes(include=[np.number]).
columns

Recompute correlation matrix for numeric columns only
interaction_correlation_matrix = train_df[numeric_cols_with_interactions].corr()

Filter correlation matrix to show interaction terms only
Ensure that both rows and columns correspond to numeric columns and available
interaction terms
interaction_correlation = interaction_correlation_matrix.loc[

```

[term for term in interaction_terms.keys() if term in
    ↪numeric_cols_with_interactions],
    [col for col in numeric_cols_with_interactions if col not in
    ↪interaction_terms.keys()]
]

# Display the correlation matrix for interaction terms
#print("\nCorrelation Matrix for Interaction Terms with Original Features:")
#print(interaction_correlation)

# Step 3: Identify and document valuable interaction terms
# Threshold for correlation strength (you can adjust this based on your
# preferences)
strong_correlation_threshold = 0.6
strong_interactions = interaction_correlation[
    interaction_correlation.abs().max(axis=1) >= strong_correlation_threshold
]

#print(f"\nStrong Interaction Terms (Correlation >
    ↪{strong_correlation_threshold}):")
#print(strong_interactions)

# Step 4: Summary of interaction terms
print("\nSummary of All Interaction Terms Created and their Corresponding
    ↪Original Features:")
for term, (f1, f2) in interaction_terms.items():
    print(f"{term}: {f1} x {f2}")

# Visualize correlation heatmap for interaction terms
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 8))
sns.heatmap(interaction_correlation, cmap='coolwarm', annot=True, fmt='.2f', ↪
    cbar=True)
plt.title("Correlation Heatmap for Interaction Terms")
plt.show()

```

Correlation Matrix for Interaction Terms with Original Features:

	Basic_Demos-Age \
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.002961
CGAS-CGAS_Score_x_Physical-BMI	0.426820
CGAS-CGAS_Score_x_Physical-Height	0.517126
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.399461
SDS-SDS_Total_Raw_x_Physical-BMI	0.321428
SDS-SDS_Total_Raw_x_Physical-Height	0.396843

SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.358217
Physical-BMI_x_Physical-Height	0.812803
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.502156
Physical-Height_x_PreInt_EduHx-computerinternet...	0.520181
Basic_Demos-Sex \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.068456
CGAS-CGAS_Score_x_Physical-BMI	0.104690
CGAS-CGAS_Score_x_Physical-Height	0.094802
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.012564
SDS-SDS_Total_Raw_x_Physical-BMI	-0.014973
SDS-SDS_Total_Raw_x_Physical-Height	-0.020312
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.001007
Physical-BMI_x_Physical-Height	0.002769
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.004259
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.000433
CGAS-CGAS_Score \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.501694
CGAS-CGAS_Score_x_Physical-BMI	0.698734
CGAS-CGAS_Score_x_Physical-Height	0.810798
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.064666
SDS-SDS_Total_Raw_x_Physical-BMI	-0.141623
SDS-SDS_Total_Raw_x_Physical-Height	-0.125426
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.109711
Physical-BMI_x_Physical-Height	-0.014462
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.093351
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.097153
Physical-BMI \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.006988
CGAS-CGAS_Score_x_Physical-BMI	0.682564
CGAS-CGAS_Score_x_Physical-Height	0.322519
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.321460
SDS-SDS_Total_Raw_x_Physical-BMI	0.583503
SDS-SDS_Total_Raw_x_Physical-Height	0.290182
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.289543
Physical-BMI_x_Physical-Height	0.927094
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.478218
Physical-Height_x_PreInt_EduHx-computerinternet...	0.388242
Physical-Height \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.002958
CGAS-CGAS_Score_x_Physical-BMI	0.434426
CGAS-CGAS_Score_x_Physical-Height	0.588934
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.375376
SDS-SDS_Total_Raw_x_Physical-BMI	0.329539
SDS-SDS_Total_Raw_x_Physical-Height	0.447196

SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.333813
Physical-BMI_x_Physical-Height	0.852275
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.456809
Physical-Height_x_PreInt_EduHx-computerinternet...	0.488695
	Physical-Weight \
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.002054
CGAS-CGAS_Score_x_Physical-BMI	0.590138
CGAS-CGAS_Score_x_Physical-Height	0.521268
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.369162
SDS-SDS_Total_Raw_x_Physical-BMI	0.486093
SDS-SDS_Total_Raw_x_Physical-Height	0.420271
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.331954
Physical-BMI_x_Physical-Height	0.984625
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.526976
Physical-Height_x_PreInt_EduHx-computerinternet...	0.503983
	Physical-Waist_Circumference
\	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.081084
CGAS-CGAS_Score_x_Physical-BMI	0.630138
CGAS-CGAS_Score_x_Physical-Height	0.492417
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.361806
SDS-SDS_Total_Raw_x_Physical-BMI	0.518215
SDS-SDS_Total_Raw_x_Physical-Height	0.390310
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.308436
Physical-BMI_x_Physical-Height	0.885278
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.466142
Physical-Height_x_PreInt_EduHx-computerinternet...	0.419725
	Physical-Diastolic_BP \
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.007453
CGAS-CGAS_Score_x_Physical-BMI	0.092192
CGAS-CGAS_Score_x_Physical-Height	0.076001
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.065202
SDS-SDS_Total_Raw_x_Physical-BMI	0.070602
SDS-SDS_Total_Raw_x_Physical-Height	0.061957
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.076338
Physical-BMI_x_Physical-Height	0.129602
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.081731
Physical-Height_x_PreInt_EduHx-computerinternet...	0.080199
	Physical-HeartRate \
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.023303
CGAS-CGAS_Score_x_Physical-BMI	-0.075406
CGAS-CGAS_Score_x_Physical-Height	-0.135298
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.055713
SDS-SDS_Total_Raw_x_Physical-BMI	-0.015939

SDS-SDS_Total_Raw_x_Physical-Height	-0.049971
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.031105
Physical-BMI_x_Physical-Height	-0.159604
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.070757
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.081553
\\	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.005151
CGAS-CGAS_Score_x_Physical-BMI	0.186441
CGAS-CGAS_Score_x_Physical-Height	0.154030
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.123042
SDS-SDS_Total_Raw_x_Physical-BMI	0.170896
SDS-SDS_Total_Raw_x_Physical-Height	0.147042
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.136640
Physical-BMI_x_Physical-Height	0.307111
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.161507
Physical-Height_x_PreInt_EduHx-computerinternet...	0.154912
\\	
Fitness_Endurance-Max_Stage	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.066838
CGAS-CGAS_Score_x_Physical-BMI	0.076601
CGAS-CGAS_Score_x_Physical-Height	0.173956
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.073570
SDS-SDS_Total_Raw_x_Physical-BMI	-0.047335
SDS-SDS_Total_Raw_x_Physical-Height	0.005089
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.084060
Physical-BMI_x_Physical-Height	-0.006644
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.094632
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.085987
\\	
Fitness_Endurance-Time_Mins	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.072055
CGAS-CGAS_Score_x_Physical-BMI	0.079370
CGAS-CGAS_Score_x_Physical-Height	0.202605
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.066590
SDS-SDS_Total_Raw_x_Physical-BMI	-0.058577
SDS-SDS_Total_Raw_x_Physical-Height	0.008240
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.080276
Physical-BMI_x_Physical-Height	-0.008894
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.093096
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.081552
\\	
Fitness_Endurance-Time_Sec	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.004665
CGAS-CGAS_Score_x_Physical-BMI	-0.049857

CGAS-CGAS_Score_x_Physical-Height	-0.075872
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.028723
SDS-SDS_Total_Raw_x_Physical-BMI	0.006672
SDS-SDS_Total_Raw_x_Physical-Height	0.004636
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.032936
Physical-BMI_x_Physical-Height	-0.058259
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.014609
Physical-Height_x_PreInt_EduHx-computerinternet...	0.024022
FGC-FGC CU \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.086699
CGAS-CGAS_Score_x_Physical-BMI	0.319985
CGAS-CGAS_Score_x_Physical-Height	0.457841
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.210201
SDS-SDS_Total_Raw_x_Physical-BMI	0.106333
SDS-SDS_Total_Raw_x_Physical-Height	0.197155
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.150474
Physical-BMI_x_Physical-Height	0.434043
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.223811
Physical-Height_x_PreInt_EduHx-computerinternet...	0.242771
FGC-FGC CU_Zone \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.093891
CGAS-CGAS_Score_x_Physical-BMI	0.048883
CGAS-CGAS_Score_x_Physical-Height	0.105286
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.063598
SDS-SDS_Total_Raw_x_Physical-BMI	-0.091276
SDS-SDS_Total_Raw_x_Physical-Height	-0.068829
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.102935
Physical-BMI_x_Physical-Height	-0.108591
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.101760
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.100419
FGC-FGC GSND \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.038287
CGAS-CGAS_Score_x_Physical-BMI	0.178643
CGAS-CGAS_Score_x_Physical-Height	0.215274
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.155271
SDS-SDS_Total_Raw_x_Physical-BMI	0.151527
SDS-SDS_Total_Raw_x_Physical-Height	0.183294
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.129494
Physical-BMI_x_Physical-Height	0.415128
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.195205
Physical-Height_x_PreInt_EduHx-computerinternet...	0.207302
FGC-FGC GSND_Zone \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.022691
CGAS-CGAS_Score_x_Physical-BMI	0.120266

CGAS-CGAS_Score_x_Physical-Height	0.053823
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.039735
SDS-SDS_Total_Raw_x_Physical-BMI	0.114199
SDS-SDS_Total_Raw_x_Physical-Height	0.068889
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.036851
Physical-BMI_x_Physical-Height	0.165901
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.009966
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.028568
FGC-FGC_GSD \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.032366
CGAS-CGAS_Score_x_Physical-BMI	0.205805
CGAS-CGAS_Score_x_Physical-Height	0.269515
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.164096
SDS-SDS_Total_Raw_x_Physical-BMI	0.160915
SDS-SDS_Total_Raw_x_Physical-Height	0.205876
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.143590
Physical-BMI_x_Physical-Height	0.481652
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.205123
Physical-Height_x_PreInt_EduHx-computerinternet...	0.223548
FGC-FGC_GSD_Zone \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.053289
CGAS-CGAS_Score_x_Physical-BMI	0.125796
CGAS-CGAS_Score_x_Physical-Height	0.087276
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.012497
SDS-SDS_Total_Raw_x_Physical-BMI	0.130151
SDS-SDS_Total_Raw_x_Physical-Height	0.098059
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.005189
Physical-BMI_x_Physical-Height	0.193049
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.017042
Physical-Height_x_PreInt_EduHx-computerinternet...	0.004936
FGC-FGC_PU \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.058790
CGAS-CGAS_Score_x_Physical-BMI	0.162705
CGAS-CGAS_Score_x_Physical-Height	0.295315
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.143622
SDS-SDS_Total_Raw_x_Physical-BMI	0.036562
SDS-SDS_Total_Raw_x_Physical-Height	0.115426
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.099104
Physical-BMI_x_Physical-Height	0.244527
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.148063
Physical-Height_x_PreInt_EduHx-computerinternet...	0.169254
FGC-FGC_PU_Zone \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.033923
CGAS-CGAS_Score_x_Physical-BMI	0.031640

CGAS-CGAS_Score_x_Physical-Height	0.109247
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.026705
SDS-SDS_Total_Raw_x_Physical-BMI	-0.051034
SDS-SDS_Total_Raw_x_Physical-Height	-0.010252
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.011559
Physical-BMI_x_Physical-Height	-0.010971
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.002737
Physical-Height_x_PreInt_EduHx-computerinternet...	0.010531
FGC-FGC_SRL \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.063995
CGAS-CGAS_Score_x_Physical-BMI	-0.035160
CGAS-CGAS_Score_x_Physical-Height	-0.081548
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.056719
SDS-SDS_Total_Raw_x_Physical-BMI	0.007240
SDS-SDS_Total_Raw_x_Physical-Height	-0.034745
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.051255
Physical-BMI_x_Physical-Height	-0.129844
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.061789
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.072242
FGC-FGC_SRL_Zone \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.029534
CGAS-CGAS_Score_x_Physical-BMI	-0.095677
CGAS-CGAS_Score_x_Physical-Height	-0.140158
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.115073
SDS-SDS_Total_Raw_x_Physical-BMI	-0.033957
SDS-SDS_Total_Raw_x_Physical-Height	-0.076661
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.097824
Physical-BMI_x_Physical-Height	-0.193163
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.112839
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.126554
FGC-FGC_SRR \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.065892
CGAS-CGAS_Score_x_Physical-BMI	-0.038346
CGAS-CGAS_Score_x_Physical-Height	-0.084542
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	-0.057747
SDS-SDS_Total_Raw_x_Physical-BMI	0.009126
SDS-SDS_Total_Raw_x_Physical-Height	-0.029952
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.043315
Physical-BMI_x_Physical-Height	-0.137555
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.065264
Physical-Height_x_PreInt_EduHx-computerintern...	-0.074696
FGC-FGC_SRR_Zone \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.045109
CGAS-CGAS_Score_x_Physical-BMI	-0.081786

CGAS-CGAS_Score_x_Physical-Height	-0.140432
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.109161
SDS-SDS_Total_Raw_x_Physical-BMI	-0.010492
SDS-SDS_Total_Raw_x_Physical-Height	-0.065717
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.082865
Physical-BMI_x_Physical-Height	-0.196329
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.108407
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.124577
FGC-FGC_TL \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.048923
CGAS-CGAS_Score_x_Physical-BMI	0.174939
CGAS-CGAS_Score_x_Physical-Height	0.223803
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.074498
SDS-SDS_Total_Raw_x_Physical-BMI	0.088840
SDS-SDS_Total_Raw_x_Physical-Height	0.118735
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.059906
Physical-BMI_x_Physical-Height	0.231766
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.080312
Physical-Height_x_PreInt_EduHx-computerinternet...	0.085294
FGC-FGC_TL_Zone \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.029625
CGAS-CGAS_Score_x_Physical-BMI	-0.031150
CGAS-CGAS_Score_x_Physical-Height	-0.018978
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.097231
SDS-SDS_Total_Raw_x_Physical-BMI	-0.058246
SDS-SDS_Total_Raw_x_Physical-Height	-0.049989
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.091286
Physical-BMI_x_Physical-Height	-0.113482
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.106096
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.108350
BIA-BIA_Activity_Level_num	
\	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.052449
CGAS-CGAS_Score_x_Physical-BMI	0.080042
CGAS-CGAS_Score_x_Physical-Height	0.158901
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.008693
SDS-SDS_Total_Raw_x_Physical-BMI	-0.013068
SDS-SDS_Total_Raw_x_Physical-Height	0.030586
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.014595
Physical-BMI_x_Physical-Height	0.076639
Physical-BMI_x_PreInt_EduHx-computerintern...	-0.006906
Physical-Height_x_PreInt_EduHx-computerintern...	0.008085
BIA-BIA_BMC BIA-BIA_BMI \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.031410 -0.009406

CGAS-CGAS_Score_x_Physical-BMI	-0.028329	0.624803	
CGAS-CGAS_Score_x_Physical-Height	-0.028320	0.303917	
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.019029	0.299650	
SDS-SDS_Total_Raw_x_Physical-BMI	-0.011892	0.558092	
SDS-SDS_Total_Raw_x_Physical-Height	-0.011226	0.289430	
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.017671	0.287149	
Physical-BMI_x_Physical-Height	-0.004881	0.858340	
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.015869	0.452796	
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.017421	0.370692	
	BIA-BIA_BMR	BIA-BIA_DEE	\
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.031384	-0.029666	
CGAS-CGAS_Score_x_Physical-BMI	0.020006	0.030761	
CGAS-CGAS_Score_x_Physical-Height	0.024129	0.042406	
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.017507	0.023216	
SDS-SDS_Total_Raw_x_Physical-BMI	0.022991	0.025830	
SDS-SDS_Total_Raw_x_Physical-Height	0.025684	0.032590	
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.011251	0.014003	
Physical-BMI_x_Physical-Height	0.082755	0.100651	
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.030736	0.036612	
Physical-Height_x_PreInt_EduHx-computerinternet...	0.029681	0.037130	
	BIA-BIA_ECW	BIA-BIA_FFM	\
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.030314	-0.031384	
CGAS-CGAS_Score_x_Physical-BMI	0.024477	0.020006	
CGAS-CGAS_Score_x_Physical-Height	0.027744	0.024129	
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.017596	0.017507	
SDS-SDS_Total_Raw_x_Physical-BMI	0.023461	0.022991	
SDS-SDS_Total_Raw_x_Physical-Height	0.025867	0.025684	
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.010116	0.011251	
Physical-BMI_x_Physical-Height	0.085760	0.082755	
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.030890	0.030736	
Physical-Height_x_PreInt_EduHx-computerinternet...	0.029718	0.029681	
	BIA-BIA_FFMI	BIA-BIA_FMI	\
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.004299	-0.000335	
CGAS-CGAS_Score_x_Physical-BMI	0.130788	0.199019	
CGAS-CGAS_Score_x_Physical-Height	0.068485	0.092076	
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.104862	0.054765	
SDS-SDS_Total_Raw_x_Physical-BMI	0.132304	0.140261	
SDS-SDS_Total_Raw_x_Physical-Height	0.079138	0.062414	
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.111270	0.029720	
Physical-BMI_x_Physical-Height	0.211643	0.242334	
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.149890	0.090665	
Physical-Height_x_PreInt_EduHx-computerinternet...	0.129067	0.068074	
	BIA-BIA_Fat	\	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.030622		

CGAS-CGAS_Score_x_Physical-BMI	0.065707	
CGAS-CGAS_Score_x_Physical-Height	0.052378	
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.038821	
SDS-SDS_Total_Raw_x_Physical-BMI	0.038831	
SDS-SDS_Total_Raw_x_Physical-Height	0.027990	
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.032744	
Physical-BMI_x_Physical-Height	0.059328	
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.044521	
Physical-Height_x_PreInt_EduHx-computerinternet...	0.042583	
	BIA-BIA_Frame_num \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.032790	
CGAS-CGAS_Score_x_Physical-BMI	0.377363	
CGAS-CGAS_Score_x_Physical-Height	0.235829	
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.173000	
SDS-SDS_Total_Raw_x_Physical-BMI	0.296638	
SDS-SDS_Total_Raw_x_Physical-Height	0.178879	
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.147006	
Physical-BMI_x_Physical-Height	0.556695	
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.258835	
Physical-Height_x_PreInt_EduHx-computerintern...	0.220168	
	BIA-BIA_ICW BIA-BIA_LDM \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.031852	-0.032036
CGAS-CGAS_Score_x_Physical-BMI	0.032126	0.005634
CGAS-CGAS_Score_x_Physical-Height	0.035178	0.011488
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.027492	0.009413
SDS-SDS_Total_Raw_x_Physical-BMI	0.035030	0.012855
SDS-SDS_Total_Raw_x_Physical-Height	0.036293	0.016978
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.020240	0.005255
Physical-BMI_x_Physical-Height	0.107332	0.059791
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.044387	0.019616
Physical-Height_x_PreInt_EduHx-computerintern...	0.042921	0.019013
	BIA-BIA_LST BIA-BIA_SMM \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.031056	-0.030968
CGAS-CGAS_Score_x_Physical-BMI	0.061538	0.034665
CGAS-CGAS_Score_x_Physical-Height	0.069168	0.036409
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.048957	0.030622
SDS-SDS_Total_Raw_x_Physical-BMI	0.052994	0.036399
SDS-SDS_Total_Raw_x_Physical-Height	0.057418	0.036525
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.036266	0.024202
Physical-BMI_x_Physical-Height	0.157541	0.108784
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.070768	0.048510
Physical-Height_x_PreInt_EduHx-computerintern...	0.070154	0.046133
	BIA-BIA_TBW \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.031009	

CGAS-CGAS_Score_x_Physical-BMI	0.027820
CGAS-CGAS_Score_x_Physical-Height	0.030998
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.021906
SDS-SDS_Total_Raw_x_Physical-BMI	0.028501
SDS-SDS_Total_Raw_x_Physical-Height	0.030413
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.014514
Physical-BMI_x_Physical-Height	0.095206
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.036775
Physical-Height_x_PreInt_EduHx-computerinternet...	0.035474
PAQ_A-PAQ_A_Total \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.060480
CGAS-CGAS_Score_x_Physical-BMI	-0.009245
CGAS-CGAS_Score_x_Physical-Height	0.075187
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.057125
SDS-SDS_Total_Raw_x_Physical-BMI	-0.150307
SDS-SDS_Total_Raw_x_Physical-Height	-0.133892
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.138913
Physical-BMI_x_Physical-Height	-0.026427
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.107023
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.084448
PAQ_C-PAQ_C_Total \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.027017
CGAS-CGAS_Score_x_Physical-BMI	0.004422
CGAS-CGAS_Score_x_Physical-Height	0.020603
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.071759
SDS-SDS_Total_Raw_x_Physical-BMI	-0.016506
SDS-SDS_Total_Raw_x_Physical-Height	-0.015271
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.071524
Physical-BMI_x_Physical-Height	0.011947
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.064380
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.076414
PCIAT-PCIAT_Total \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.144338
CGAS-CGAS_Score_x_Physical-BMI	0.142928
CGAS-CGAS_Score_x_Physical-Height	0.171662
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.353586
SDS-SDS_Total_Raw_x_Physical-BMI	0.345330
SDS-SDS_Total_Raw_x_Physical-Height	0.389279
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.385682
Physical-BMI_x_Physical-Height	0.366443
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.374872
Physical-Height_x_PreInt_EduHx-computerinternet...	0.389992
SDS-SDS_Total_Raw \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.773868

CGAS-CGAS_Score_x_Physical-BMI	-0.082695
CGAS-CGAS_Score_x_Physical-Height	-0.112729
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.057740
SDS-SDS_Total_Raw_x_Physical-BMI	0.818866
SDS-SDS_Total_Raw_x_Physical-Height	0.890367
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.290390
Physical-BMI_x_Physical-Height	0.023975
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.087531
Physical-Height_x_PreInt_EduHx-computerinternet...	0.089659
SDS-SDS_Total_T \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.769768
CGAS-CGAS_Score_x_Physical-BMI	-0.083618
CGAS-CGAS_Score_x_Physical-Height	-0.113016
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.059738
SDS-SDS_Total_Raw_x_Physical-BMI	0.817832
SDS-SDS_Total_Raw_x_Physical-Height	0.890481
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.294082
Physical-BMI_x_Physical-Height	0.025761
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.090256
Physical-Height_x_PreInt_EduHx-computerinternet...	0.092612
PreInt_EduHx-	
computerinternet_hoursday \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	
0.020153	
CGAS-CGAS_Score_x_Physical-BMI	
0.159345	
CGAS-CGAS_Score_x_Physical-Height	
0.136174	
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	
0.971988	
SDS-SDS_Total_Raw_x_Physical-BMI	
0.242763	
SDS-SDS_Total_Raw_x_Physical-Height	
0.242915	
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	
0.949283	
Physical-BMI_x_Physical-Height	
0.392167	
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	
0.972717	
Physical-Height_x_PreInt_EduHx-computerinternet...	
0.985726	
sii PCIAT_Cluster	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.127202 0.037397
CGAS-CGAS_Score_x_Physical-BMI	0.131911 0.091335

CGAS-CGAS_Score_x_Physical-Height	0.143135	0.109724
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.326892	0.177675
SDS-SDS_Total_Raw_x_Physical-BMI	0.335201	0.132452
SDS-SDS_Total_Raw_x_Physical-Height	0.366807	0.147515
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.352190	0.179416
Physical-BMI_x_Physical-Height	0.359416	0.197982
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.354085	0.198325
Physical-Height_x_PreInt_EduHx-computerinternet...	0.365949	0.207116

Strong Interaction Terms (Correlation > 0.6):

	Basic_Demos-Age \
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.002961
CGAS-CGAS_Score_x_Physical-BMI	0.426820
CGAS-CGAS_Score_x_Physical-Height	0.517126
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.399461
SDS-SDS_Total_Raw_x_Physical-BMI	0.321428
SDS-SDS_Total_Raw_x_Physical-Height	0.396843
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.358217
Physical-BMI_x_Physical-Height	0.812803
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.502156
Physical-Height_x_PreInt_EduHx-computerinternet...	0.520181

	Basic_Demos-Sex \
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.068456
CGAS-CGAS_Score_x_Physical-BMI	0.104690
CGAS-CGAS_Score_x_Physical-Height	0.094802
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.012564
SDS-SDS_Total_Raw_x_Physical-BMI	-0.014973
SDS-SDS_Total_Raw_x_Physical-Height	-0.020312
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.001007
Physical-BMI_x_Physical-Height	0.002769
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.004259
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.000433

	CGAS-CGAS_Score \
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.501694
CGAS-CGAS_Score_x_Physical-BMI	0.698734
CGAS-CGAS_Score_x_Physical-Height	0.810798
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.064666
SDS-SDS_Total_Raw_x_Physical-BMI	-0.141623
SDS-SDS_Total_Raw_x_Physical-Height	-0.125426
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.109711
Physical-BMI_x_Physical-Height	-0.014462
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.093351
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.097153

	Physical-BMI \
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.006988

CGAS-CGAS_Score_x_Physical-BMI	0.682564
CGAS-CGAS_Score_x_Physical-Height	0.322519
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.321460
SDS-SDS_Total_Raw_x_Physical-BMI	0.583503
SDS-SDS_Total_Raw_x_Physical-Height	0.290182
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.289543
Physical-BMI_x_Physical-Height	0.927094
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.478218
Physical-Height_x_PreInt_EduHx-computerinternet...	0.388242
Physical-Height \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.002958
CGAS-CGAS_Score_x_Physical-BMI	0.434426
CGAS-CGAS_Score_x_Physical-Height	0.588934
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.375376
SDS-SDS_Total_Raw_x_Physical-BMI	0.329539
SDS-SDS_Total_Raw_x_Physical-Height	0.447196
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.333813
Physical-BMI_x_Physical-Height	0.852275
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.456809
Physical-Height_x_PreInt_EduHx-computerinternet...	0.488695
Physical-Weight \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.002054
CGAS-CGAS_Score_x_Physical-BMI	0.590138
CGAS-CGAS_Score_x_Physical-Height	0.521268
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.369162
SDS-SDS_Total_Raw_x_Physical-BMI	0.486093
SDS-SDS_Total_Raw_x_Physical-Height	0.420271
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.331954
Physical-BMI_x_Physical-Height	0.984625
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.526976
Physical-Height_x_PreInt_EduHx-computerinternet...	0.503983
Physical-Waist_Circumference	
\	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.081084
CGAS-CGAS_Score_x_Physical-BMI	0.630138
CGAS-CGAS_Score_x_Physical-Height	0.492417
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.361806
SDS-SDS_Total_Raw_x_Physical-BMI	0.518215
SDS-SDS_Total_Raw_x_Physical-Height	0.390310
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.308436
Physical-BMI_x_Physical-Height	0.885278
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.466142
Physical-Height_x_PreInt_EduHx-computerinternet...	0.419725
Physical-Diastolic_BP \	

CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.007453
CGAS-CGAS_Score_x_Physical-BMI	0.092192
CGAS-CGAS_Score_x_Physical-Height	0.076001
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.065202
SDS-SDS_Total_Raw_x_Physical-BMI	0.070602
SDS-SDS_Total_Raw_x_Physical-Height	0.061957
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.076338
Physical-BMI_x_Physical-Height	0.129602
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.081731
Physical-Height_x_PreInt_EduHx-computerinternet...	0.080199
Physical-HeartRate \	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.023303
CGAS-CGAS_Score_x_Physical-BMI	-0.075406
CGAS-CGAS_Score_x_Physical-Height	-0.135298
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.055713
SDS-SDS_Total_Raw_x_Physical-BMI	-0.015939
SDS-SDS_Total_Raw_x_Physical-Height	-0.049971
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.031105
Physical-BMI_x_Physical-Height	-0.159604
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.070757
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.081553
Physical-Systolic_BP \	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.005151
CGAS-CGAS_Score_x_Physical-BMI	0.186441
CGAS-CGAS_Score_x_Physical-Height	0.154030
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.123042
SDS-SDS_Total_Raw_x_Physical-BMI	0.170896
SDS-SDS_Total_Raw_x_Physical-Height	0.147042
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.136640
Physical-BMI_x_Physical-Height	0.307111
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.161507
Physical-Height_x_PreInt_EduHx-computerinternet...	0.154912
Fitness_Endurance-Max_Stage	
\	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.066838
CGAS-CGAS_Score_x_Physical-BMI	0.076601
CGAS-CGAS_Score_x_Physical-Height	0.173956
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.073570
SDS-SDS_Total_Raw_x_Physical-BMI	-0.047335
SDS-SDS_Total_Raw_x_Physical-Height	0.005089
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.084060
Physical-BMI_x_Physical-Height	-0.006644
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.094632
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.085987

	Fitness_Endurance-Time_Mins
\	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.072055
CGAS-CGAS_Score_x_Physical-BMI	0.079370
CGAS-CGAS_Score_x_Physical-Height	0.202605
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.066590
SDS-SDS_Total_Raw_x_Physical-BMI	-0.058577
SDS-SDS_Total_Raw_x_Physical-Height	0.008240
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.080276
Physical-BMI_x_Physical-Height	-0.008894
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.093096
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.081552
	Fitness_Endurance-Time_Sec
\	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.004665
CGAS-CGAS_Score_x_Physical-BMI	-0.049857
CGAS-CGAS_Score_x_Physical-Height	-0.075872
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.028723
SDS-SDS_Total_Raw_x_Physical-BMI	0.006672
SDS-SDS_Total_Raw_x_Physical-Height	0.004636
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.032936
Physical-BMI_x_Physical-Height	-0.058259
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.014609
Physical-Height_x_PreInt_EduHx-computerinternet...	0.024022
	FCC-FGC CU \
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.086699
CGAS-CGAS_Score_x_Physical-BMI	0.319985
CGAS-CGAS_Score_x_Physical-Height	0.457841
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.210201
SDS-SDS_Total_Raw_x_Physical-BMI	0.106333
SDS-SDS_Total_Raw_x_Physical-Height	0.197155
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.150474
Physical-BMI_x_Physical-Height	0.434043
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.223811
Physical-Height_x_PreInt_EduHx-computerinternet...	0.242771
	FCC-FGC CU_Zone \
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.093891
CGAS-CGAS_Score_x_Physical-BMI	0.048883
CGAS-CGAS_Score_x_Physical-Height	0.105286
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	-0.063598
SDS-SDS_Total_Raw_x_Physical-BMI	-0.091276
SDS-SDS_Total_Raw_x_Physical-Height	-0.068829
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.102935
Physical-BMI_x_Physical-Height	-0.108591
Physical-BMI_x_PreInt_EduHx-computerintern...	-0.101760

Physical-Height_x_PreInt_EduHx-computerinternet...	-0.100419
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.038287
CGAS-CGAS_Score_x_Physical-BMI	0.178643
CGAS-CGAS_Score_x_Physical-Height	0.215274
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.155271
SDS-SDS_Total_Raw_x_Physical-BMI	0.151527
SDS-SDS_Total_Raw_x_Physical-Height	0.183294
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.129494
Physical-BMI_x_Physical-Height	0.415128
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.195205
Physical-Height_x_PreInt_EduHx-computerinternet...	0.207302
FGC-FGC_GSND \	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.022691
CGAS-CGAS_Score_x_Physical-BMI	0.120266
CGAS-CGAS_Score_x_Physical-Height	0.053823
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.039735
SDS-SDS_Total_Raw_x_Physical-BMI	0.114199
SDS-SDS_Total_Raw_x_Physical-Height	0.068889
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.036851
Physical-BMI_x_Physical-Height	0.165901
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.009966
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.028568
FGC-FGC_GSND_Zone \	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.032366
CGAS-CGAS_Score_x_Physical-BMI	0.205805
CGAS-CGAS_Score_x_Physical-Height	0.269515
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.164096
SDS-SDS_Total_Raw_x_Physical-BMI	0.160915
SDS-SDS_Total_Raw_x_Physical-Height	0.205876
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.143590
Physical-BMI_x_Physical-Height	0.481652
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.205123
Physical-Height_x_PreInt_EduHx-computerinternet...	0.223548
FGC-FGC_GSD \	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.053289
CGAS-CGAS_Score_x_Physical-BMI	0.125796
CGAS-CGAS_Score_x_Physical-Height	0.087276
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.012497
SDS-SDS_Total_Raw_x_Physical-BMI	0.130151
SDS-SDS_Total_Raw_x_Physical-Height	0.098059
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.005189
Physical-BMI_x_Physical-Height	0.193049
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.017042
FGC-FGC_GSD_Zone \	

Physical-Height_x_PreInt_EduHx-computerinternet...	0.004936
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	FGC-FGC_PU \ 0.058790
CGAS-CGAS_Score_x_Physical-BMI	0.162705
CGAS-CGAS_Score_x_Physical-Height	0.295315
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.143622
SDS-SDS_Total_Raw_x_Physical-BMI	0.036562
SDS-SDS_Total_Raw_x_Physical-Height	0.115426
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.099104
Physical-BMI_x_Physical-Height	0.244527
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.148063
Physical-Height_x_PreInt_EduHx-computerinternet...	0.169254
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	FGC-FGC_PU_Zone \ 0.033923
CGAS-CGAS_Score_x_Physical-BMI	0.031640
CGAS-CGAS_Score_x_Physical-Height	0.109247
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.026705
SDS-SDS_Total_Raw_x_Physical-BMI	-0.051034
SDS-SDS_Total_Raw_x_Physical-Height	-0.010252
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.011559
Physical-BMI_x_Physical-Height	-0.010971
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.002737
Physical-Height_x_PreInt_EduHx-computerinternet...	0.010531
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	FGC-FGC_SRL \ 0.063995
CGAS-CGAS_Score_x_Physical-BMI	-0.035160
CGAS-CGAS_Score_x_Physical-Height	-0.081548
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.056719
SDS-SDS_Total_Raw_x_Physical-BMI	0.007240
SDS-SDS_Total_Raw_x_Physical-Height	-0.034745
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.051255
Physical-BMI_x_Physical-Height	-0.129844
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.061789
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.072242
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	FGC-FGC_SRL_Zone \ 0.029534
CGAS-CGAS_Score_x_Physical-BMI	-0.095677
CGAS-CGAS_Score_x_Physical-Height	-0.140158
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	-0.115073
SDS-SDS_Total_Raw_x_Physical-BMI	-0.033957
SDS-SDS_Total_Raw_x_Physical-Height	-0.076661
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.097824
Physical-BMI_x_Physical-Height	-0.193163
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.112839

Physical-Height_x_PreInt_EduHx-computerinternet...	-0.126554
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.065892
CGAS-CGAS_Score_x_Physical-BMI	-0.038346
CGAS-CGAS_Score_x_Physical-Height	-0.084542
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.057747
SDS-SDS_Total_Raw_x_Physical-BMI	0.009126
SDS-SDS_Total_Raw_x_Physical-Height	-0.029952
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.043315
Physical-BMI_x_Physical-Height	-0.137555
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.065264
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.074696
FGC-FGC_SRR \	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.045109
CGAS-CGAS_Score_x_Physical-BMI	-0.081786
CGAS-CGAS_Score_x_Physical-Height	-0.140432
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.109161
SDS-SDS_Total_Raw_x_Physical-BMI	-0.010492
SDS-SDS_Total_Raw_x_Physical-Height	-0.065717
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.082865
Physical-BMI_x_Physical-Height	-0.196329
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.108407
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.124577
FGC-FGC_SRR_Zone \	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.048923
CGAS-CGAS_Score_x_Physical-BMI	0.174939
CGAS-CGAS_Score_x_Physical-Height	0.223803
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.074498
SDS-SDS_Total_Raw_x_Physical-BMI	0.088840
SDS-SDS_Total_Raw_x_Physical-Height	0.118735
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.059906
Physical-BMI_x_Physical-Height	0.231766
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.080312
Physical-Height_x_PreInt_EduHx-computerinternet...	0.085294
FGC-FGC_TL \	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.029625
CGAS-CGAS_Score_x_Physical-BMI	-0.031150
CGAS-CGAS_Score_x_Physical-Height	-0.018978
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.097231
SDS-SDS_Total_Raw_x_Physical-BMI	-0.058246
SDS-SDS_Total_Raw_x_Physical-Height	-0.049989
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.091286
Physical-BMI_x_Physical-Height	-0.113482
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.106096
FGC-FGC_TL_Zone \	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.029625
CGAS-CGAS_Score_x_Physical-BMI	-0.031150
CGAS-CGAS_Score_x_Physical-Height	-0.018978
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	-0.097231
SDS-SDS_Total_Raw_x_Physical-BMI	-0.058246
SDS-SDS_Total_Raw_x_Physical-Height	-0.049989
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.091286
Physical-BMI_x_Physical-Height	-0.113482
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.106096

Physical-Height_x_PreInt_EduHx-computerinternet...	-0.108350	
		BIA-BIA_Activity_Level_num
\		
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.052449	
CGAS-CGAS_Score_x_Physical-BMI	0.080042	
CGAS-CGAS_Score_x_Physical-Height	0.158901	
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.008693	
SDS-SDS_Total_Raw_x_Physical-BMI	-0.013068	
SDS-SDS_Total_Raw_x_Physical-Height	0.030586	
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.014595	
Physical-BMI_x_Physical-Height	0.076639	
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.006906	
Physical-Height_x_PreInt_EduHx-computerinternet...	0.008085	
		BIA-BIA_BMC BIA-BIA_BMI \
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.031410	-0.009406
CGAS-CGAS_Score_x_Physical-BMI	-0.028329	0.624803
CGAS-CGAS_Score_x_Physical-Height	-0.028320	0.303917
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	-0.019029	0.299650
SDS-SDS_Total_Raw_x_Physical-BMI	-0.011892	0.558092
SDS-SDS_Total_Raw_x_Physical-Height	-0.011226	0.289430
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.017671	0.287149
Physical-BMI_x_Physical-Height	-0.004881	0.858340
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.015869	0.452796
Physical-Height_x_PreInt_EduHx-computerintern...	-0.017421	0.370692
		BIA-BIA_BMR BIA-BIA_DEE \
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.031384	-0.029666
CGAS-CGAS_Score_x_Physical-BMI	0.020006	0.030761
CGAS-CGAS_Score_x_Physical-Height	0.024129	0.042406
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.017507	0.023216
SDS-SDS_Total_Raw_x_Physical-BMI	0.022991	0.025830
SDS-SDS_Total_Raw_x_Physical-Height	0.025684	0.032590
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.011251	0.014003
Physical-BMI_x_Physical-Height	0.082755	0.100651
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.030736	0.036612
Physical-Height_x_PreInt_EduHx-computerintern...	0.029681	0.037130
		BIA-BIA_ECW BIA-BIA_FFM \
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	-0.030314	-0.031384
CGAS-CGAS_Score_x_Physical-BMI	0.024477	0.020006
CGAS-CGAS_Score_x_Physical-Height	0.027744	0.024129
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.017596	0.017507
SDS-SDS_Total_Raw_x_Physical-BMI	0.023461	0.022991
SDS-SDS_Total_Raw_x_Physical-Height	0.025867	0.025684
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.010116	0.011251
Physical-BMI_x_Physical-Height	0.085760	0.082755

Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.030890	0.030736	
Physical-Height_x_PreInt_EduHx-computerinternet...	0.029718	0.029681	
	BIA-BIA_FFMI	BIA-BIA_FMI	\
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	-0.004299	-0.000335	
CGAS-CGAS_Score_x_Physical-BMI	0.130788	0.199019	
CGAS-CGAS_Score_x_Physical-Height	0.068485	0.092076	
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.104862	0.054765	
SDS-SDS_Total_Raw_x_Physical-BMI	0.132304	0.140261	
SDS-SDS_Total_Raw_x_Physical-Height	0.079138	0.062414	
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.111270	0.029720	
Physical-BMI_x_Physical-Height	0.211643	0.242334	
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.149890	0.090665	
Physical-Height_x_PreInt_EduHx-computerinternet...	0.129067	0.068074	
	BIA-BIA_Fat	\	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	0.030622		
CGAS-CGAS_Score_x_Physical-BMI	0.065707		
CGAS-CGAS_Score_x_Physical-Height	0.052378		
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.038821		
SDS-SDS_Total_Raw_x_Physical-BMI	0.038831		
SDS-SDS_Total_Raw_x_Physical-Height	0.027990		
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.032744		
Physical-BMI_x_Physical-Height	0.059328		
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.044521		
Physical-Height_x_PreInt_EduHx-computerintern...	0.042583		
	BIA-BIA_Frame_num	\	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	-0.032790		
CGAS-CGAS_Score_x_Physical-BMI	0.377363		
CGAS-CGAS_Score_x_Physical-Height	0.235829		
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.173000		
SDS-SDS_Total_Raw_x_Physical-BMI	0.296638		
SDS-SDS_Total_Raw_x_Physical-Height	0.178879		
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.147006		
Physical-BMI_x_Physical-Height	0.556695		
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.258835		
Physical-Height_x_PreInt_EduHx-computerintern...	0.220168		
	BIA-BIA_ICW	BIA-BIA_LDM	\
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	-0.031852	-0.032036	
CGAS-CGAS_Score_x_Physical-BMI	0.032126	0.005634	
CGAS-CGAS_Score_x_Physical-Height	0.035178	0.011488	
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.027492	0.009413	
SDS-SDS_Total_Raw_x_Physical-BMI	0.035030	0.012855	
SDS-SDS_Total_Raw_x_Physical-Height	0.036293	0.016978	
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.020240	0.005255	
Physical-BMI_x_Physical-Height	0.107332	0.059791	

Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.044387	0.019616	
Physical-Height_x_PreInt_EduHx-computerinternet...	0.042921	0.019013	
	BIA-BIA_LST	BIA-BIA_SMM	\
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	-0.031056	-0.030968	
CGAS-CGAS_Score_x_Physical-BMI	0.061538	0.034665	
CGAS-CGAS_Score_x_Physical-Height	0.069168	0.036409	
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.048957	0.030622	
SDS-SDS_Total_Raw_x_Physical-BMI	0.052994	0.036399	
SDS-SDS_Total_Raw_x_Physical-Height	0.057418	0.036525	
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.036266	0.024202	
Physical-BMI_x_Physical-Height	0.157541	0.108784	
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.070768	0.048510	
Physical-Height_x_PreInt_EduHx-computerinternet...	0.070154	0.046133	
	BIA-BIA_TBW	\	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	-0.031009		
CGAS-CGAS_Score_x_Physical-BMI	0.027820		
CGAS-CGAS_Score_x_Physical-Height	0.030998		
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.021906		
SDS-SDS_Total_Raw_x_Physical-BMI	0.028501		
SDS-SDS_Total_Raw_x_Physical-Height	0.030413		
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.014514		
Physical-BMI_x_Physical-Height	0.095206		
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.036775		
Physical-Height_x_PreInt_EduHx-computerintern...	0.035474		
	PAQ_A-PAQ_A_Total	\	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	-0.060480		
CGAS-CGAS_Score_x_Physical-BMI	-0.009245		
CGAS-CGAS_Score_x_Physical-Height	0.075187		
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	-0.057125		
SDS-SDS_Total_Raw_x_Physical-BMI	-0.150307		
SDS-SDS_Total_Raw_x_Physical-Height	-0.133892		
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.138913		
Physical-BMI_x_Physical-Height	-0.026427		
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.107023		
Physical-Height_x_PreInt_EduHx-computerintern...	-0.084448		
	PAQ_C-PAQ_C_Total	\	
CGAS-CGAS_Score_x SDS-SDS_Total_Raw	-0.027017		
CGAS-CGAS_Score_x_Physical-BMI	0.004422		
CGAS-CGAS_Score_x_Physical-Height	0.020603		
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	-0.071759		
SDS-SDS_Total_Raw_x_Physical-BMI	-0.016506		
SDS-SDS_Total_Raw_x_Physical-Height	-0.015271		
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	-0.071524		
Physical-BMI_x_Physical-Height	0.011947		

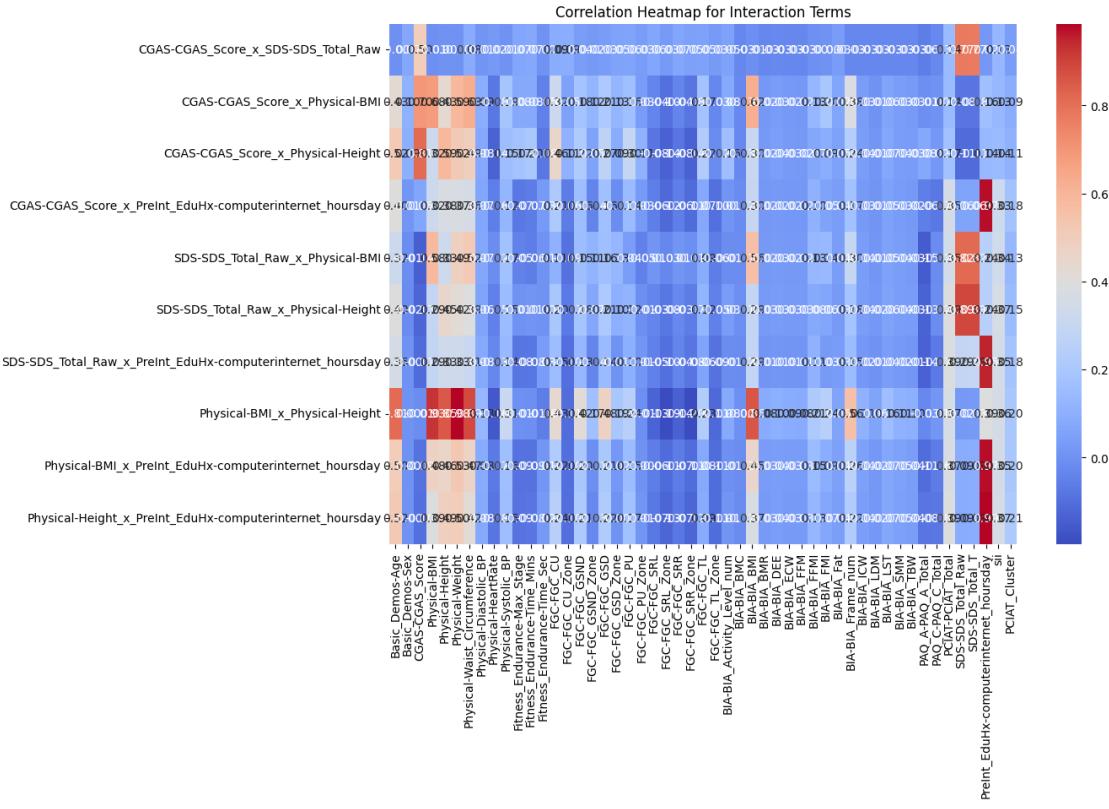
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	-0.064380
Physical-Height_x_PreInt_EduHx-computerinternet...	-0.076414
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.144338
CGAS-CGAS_Score_x_Physical-BMI	0.142928
CGAS-CGAS_Score_x_Physical-Height	0.171662
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.353586
SDS-SDS_Total_Raw_x_Physical-BMI	0.345330
SDS-SDS_Total_Raw_x_Physical-Height	0.389279
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.385682
Physical-BMI_x_Physical-Height	0.366443
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.374872
Physical-Height_x_PreInt_EduHx-computerinternet...	0.389992
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.773868
CGAS-CGAS_Score_x_Physical-BMI	-0.082695
CGAS-CGAS_Score_x_Physical-Height	-0.112729
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.057740
SDS-SDS_Total_Raw_x_Physical-BMI	0.818866
SDS-SDS_Total_Raw_x_Physical-Height	0.890367
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.290390
Physical-BMI_x_Physical-Height	0.023975
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.087531
Physical-Height_x_PreInt_EduHx-computerintern...	0.089659
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.769768
CGAS-CGAS_Score_x_Physical-BMI	-0.083618
CGAS-CGAS_Score_x_Physical-Height	-0.113016
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	0.059738
SDS-SDS_Total_Raw_x_Physical-BMI	0.817832
SDS-SDS_Total_Raw_x_Physical-Height	0.890481
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...	0.294082
Physical-BMI_x_Physical-Height	0.025761
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.090256
Physical-Height_x_PreInt_EduHx-computerintern...	0.092612
computerinternet_hoursday \	
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	
0.020153	
CGAS-CGAS_Score_x_Physical-BMI	
0.159345	
CGAS-CGAS_Score_x_Physical-Height	
0.136174	
CGAS-CGAS_Score_x_PreInt_EduHx-computerintern...	

0.971988
 SDS-SDS_Total_Raw_x_Physical-BMI
 0.242763
 SDS-SDS_Total_Raw_x_Physical-Height
 0.242915
 SDS-SDS_Total_Raw_x_PreInt_EduHx-computerintern...
 0.949283
 Physical-BMI_x_Physical-Height
 0.392167
 Physical-BMI_x_PreInt_EduHx-computerinternet_ho...
 0.972717
 Physical-Height_x_PreInt_EduHx-computerinternet...
 0.985726

	sii	PCIAT_Cluster
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	0.127202	0.037397
CGAS-CGAS_Score_x_Physical-BMI	0.131911	0.091335
CGAS-CGAS_Score_x_Physical-Height	0.143135	0.109724
CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet...	0.326892	0.177675
SDS-SDS_Total_Raw_x_Physical-BMI	0.335201	0.132452
SDS-SDS_Total_Raw_x_Physical-Height	0.366807	0.147515
SDS-SDS_Total_Raw_x_PreInt_EduHx-computerinternet...	0.352190	0.179416
Physical-BMI_x_Physical-Height	0.359416	0.197982
Physical-BMI_x_PreInt_EduHx-computerinternet_ho...	0.354085	0.198325
Physical-Height_x_PreInt_EduHx-computerinternet...	0.365949	0.207116

Summary of All Interaction Terms Created and their Corresponding Original Features:

CGAS-CGAS_Score_x_SDS-SDS_Total_Raw: CGAS-CGAS_Score x SDS-SDS_Total_Raw
 CGAS-CGAS_Score_x_Physical-BMI: CGAS-CGAS_Score x Physical-BMI
 CGAS-CGAS_Score_x_Physical-Height: CGAS-CGAS_Score x Physical-Height
 CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet_hoursday: CGAS-CGAS_Score x PreInt_EduHx-computerinternet_hoursday
 SDS-SDS_Total_Raw_x_Physical-BMI: SDS-SDS_Total_Raw x Physical-BMI
 SDS-SDS_Total_Raw_x_Physical-Height: SDS-SDS_Total_Raw x Physical-Height
 SDS-SDS_Total_Raw_x_PreInt_EduHx-computerinternet_hoursday: SDS-SDS_Total_Raw x PreInt_EduHx-computerinternet_hoursday
 Physical-BMI_x_Physical-Height: Physical-BMI x Physical-Height
 Physical-BMI_x_PreInt_EduHx-computerinternet_hoursday: Physical-BMI x PreInt_EduHx-computerinternet_hoursday
 Physical-Height_x_PreInt_EduHx-computerinternet_hoursday: Physical-Height x PreInt_EduHx-computerinternet_hoursday



Key Insights High Correlation Among Interaction Terms and Original Features:

Several interaction terms show strong correlations (above 0.6) with original features. For example: Physical-BMI_x_Physical-Height has a very high correlation with both Physical-BMI (0.927) and Physical-Height (0.852), suggesting that this interaction term might not provide additional value since it's heavily dependent on the two original features. Interaction terms like CGAS-CGAS_Score_x_Physical-Height and SDS-SDS_Total_Raw_x_Physical-Height also show high correlations with their original features, which could imply that these interaction terms may not add unique information to the model.

Relationship of Interaction Terms with Key Outcome Variables:

Interaction terms like CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet_hoursday show moderate correlations with outcome variables like PCIAT-PCIAT_Total (0.354) and sii (0.326). This indicates that some interaction terms do have a significant relationship with key outcomes, but the strength of these correlations is not overwhelmingly strong, suggesting that further refinement is needed. Multicollinearity Concerns:

Interaction terms involving Physical-BMI, Physical-Height, and PreInt_EduHx-computerinternet_hoursday show high correlations with each other (e.g., Physical-BMI_x_Physical-Height has a correlation of 0.812 with Physical-BMI and 0.852 with Physical-Height). This could introduce multicollinearity in the model, which could negatively impact model stability and interpretability. Low Correlation with Certain Outcome Variables:

Several interaction terms show low correlation values (less than 0.2) with the PCIAT-Cluster variable. For instance, CGAS-CGAS_Score_x_Physical-BMI and Physical-Height_x_PreInt_EduHx-computerinternet_hoursday have correlation values around 0.1-0.19 with PCIAT-Cluster. This suggests that these interaction terms may not be particularly useful for predicting PCIAT-Cluster.

```
[25]: !pip install category_encoders --quiet

from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
import category_encoders as ce # for target encoding
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Step 1: Remove redundant interaction terms based on correlation analysis
# Define threshold for high correlation
high_corr_threshold = 0.8
target_columns = ['PCIAT-PCIAT_Total', 'sii', 'PCIAT_Cluster']

# Identify redundant interaction terms
redundant_terms = []
for term, (f1, f2) in interaction_terms.items():
    # Calculate correlation between interaction term and its original features
    corr_with_f1 = train_df[term].corr(train_df[f1])
    corr_with_f2 = train_df[term].corr(train_df[f2])

    # Check if either correlation exceeds the threshold
    if abs(corr_with_f1) >= high_corr_threshold or abs(corr_with_f2) >=
        ↪high_corr_threshold:
        redundant_terms.append(term)

# Drop redundant interaction terms and print the count
train_df.drop(columns=redundant_terms, inplace=True)
print(f"Redundant interaction terms removed: {redundant_terms}")
print(f"Remaining columns after removing redundant interaction terms: {train_df.
    ↪columns}")

# Step 2: Impute missing values using MICE
# Use IterativeImputer to perform MICE imputation on numeric columns
numeric_features = train_df.select_dtypes(include=[np.number]).columns
mice_imputer = IterativeImputer(max_iter=10, random_state=42) # Configure MICE
    ↪imputer
imputed_values = mice_imputer.fit_transform(train_df[numeric_features])

# Replace original DataFrame's numeric columns with MICE-imputed values
train_df[numeric_features] = imputed_values
print(f"Remaining columns after MICE imputation: {train_df.columns}")
```

```

# Step 3: Apply Target Encoding to categorical features
# Identify categorical features
categorical_features = train_df.select_dtypes(include=['category', 'object']).columns

# Check if categorical features exist
if len(categorical_features) > 0:
    print(f"Categorical features identified: {categorical_features}")

    # Use target encoding for categorical features based on the target variable
    # 'sii'
    target_encoder = ce.TargetEncoder(cols=categorical_features)
    # Fit and transform the categorical features
    train_df[categorical_features] = target_encoder.
    #fit_transform(train_df[categorical_features], train_df['sii'])

else:
    print("No categorical features found for encoding.")

# Step 4: Implement VIF analysis to identify multicollinearity issues

# Check for infinite values and replace with NaN
train_df.replace([np.inf, -np.inf], np.nan, inplace=True)

# Create a DataFrame for VIF calculation (exclude non-numeric columns)
vif_features = train_df.select_dtypes(include=[np.number]).columns

# Ensure there are no missing or infinite values in the VIF features
vif_features_cleaned = train_df[vif_features].dropna().columns
print(f"Features to be included in VIF analysis: {vif_features_cleaned}")

# Calculate VIF values
vif_df = pd.DataFrame()
vif_df['Feature'] = vif_features_cleaned
vif_df['VIF'] = [variance_inflation_factor(train_df[vif_features_cleaned].
    #values, i) for i in range(len(vif_features_cleaned))]

print(f"VIF values for features:\n{vif_df}")

# Step 5: Remove features with high VIF (> 10)
high_vif_features = vif_df[vif_df['VIF'] > 10]['Feature'].tolist()
print(f"Features marked for removal due to high VIF: {high_vif_features}")

# Ensure that we don't remove all features
if len(high_vif_features) >= len(train_df.columns) - len(target_columns):
    print("Warning: Attempting to remove too many features. Adjusting VIF
    #threshold to retain features.")

    high_vif_features = [] # Do not remove any features if this condition is
    #met

```

```

# Remove high VIF features and print remaining columns
train_df.drop(columns=high_vif_features, inplace=True)
print(f"Remaining columns after removing high VIF features: {train_df.columns}")

# Step 6: Create missingness indicator columns
# Define threshold for missingness
missing_threshold = 0.1

# Create missingness indicator columns
for col in train_df.columns:
    missing_ratio = train_df[col].isnull().mean()
    if missing_ratio >= missing_threshold:
        # Create missingness indicator
        missing_indicator_col = f"{col}_missing"
        train_df[missing_indicator_col] = train_df[col].isnull().astype(int)
        print(f"Created missingness indicator for {col} (Missing Ratio:{missing_ratio:.2f})")

print(f"Remaining columns after creating missingness indicators: {train_df.columns}")

# Step 7: Reevaluate correlation of selected features with target variables
target_columns = ['PCIAT-PCIAT_Total', 'sii', 'PCIAT_Cluster']

# Filter only numeric columns before running correlation analysis
numeric_df = train_df.select_dtypes(include=[np.number])

# Ensure that target columns exist in the numeric DataFrame
for target in target_columns:
    if target not in numeric_df.columns:
        print(f"Warning: Target column '{target}' is missing from the DataFrame.
        Ensure it is not dropped inadvertently.")

# Calculate the correlation matrix only on numeric columns
interaction_correlation_matrix = numeric_df.corr()

# Filter interaction terms that remain after the previous steps
remaining_interaction_terms = [term for term in interaction_terms.keys() if
    term not in redundant_terms and term not in high_vif_features]

# Calculate correlation with target variables
for target in target_columns:
    if target in numeric_df.columns:
        print(f"\nCorrelation of remaining interaction terms with {target}:")
        for term in remaining_interaction_terms:
            if term in numeric_df.columns:

```

```

corr_value = numeric_df[term].corr(numeric_df[target])
print(f'{term}: {corr_value:.4f}')

```

Redundant interaction terms removed: ['CGAS-CGAS_Score_x_Physical-Height', 'CGAS-CGAS_Score_x_PreInt_EduHx-computerinternet_hoursday', 'SDS-SDS_Total_Raw_x_Physical-BMI', 'SDS-SDS_Total_Raw_x_Physical-Height', 'SDS-SDS_Total_Raw_x_PreInt_EduHx-computerinternet_hoursday', 'Physical-BMI_x_Physical-Height', 'Physical-BMI_x_PreInt_EduHx-computerinternet_hoursday', 'Physical-Height_x_PreInt_EduHx-computerinternet_hoursday']

Remaining columns after removing redundant interaction terms: Index(['id', 'Basic_Demos-Enroll_Season', 'Basic_Demos-Age', 'Basic_Demos-Sex', 'CGAS-Season', 'CGAS-CGAS_Score', 'Physical-Season', 'Physical-BMI', 'Physical-Height', 'Physical-Weight', 'Physical-Waist_Circumference', 'Physical-Diastolic_BP', 'Physical-HeartRate', 'Physical-Systolic_BP', 'Fitness_Endurance-Season', 'Fitness_Endurance-Max_Stage', 'Fitness_Endurance-Time_Mins', 'Fitness_Endurance-Time_Sec', 'FGC-Season', 'FGC-FGC CU', 'FGC-FGC CU_Zone', 'FGC-FGC GSND', 'FGC-FGC GSND_Zone', 'FGC-FGC GSD', 'FGC-FGC GSD_Zone', 'FGC-FGC PU', 'FGC-FGC PU_Zone', 'FGC-FGC SRL', 'FGC-FGC SRL_Zone', 'FGC-FGC SRR', 'FGC-FGC SRR_Zone', 'FGC-FGC TL', 'FGC-FGC TL_Zone', 'BIA-Season', 'BIA-BIA_Activity_Level_num', 'BIA-BIA_BMC', 'BIA-BIA_BMI', 'BIA-BIA_BMR', 'BIA-BIA_DEE', 'BIA-BIA_ECW', 'BIA-BIA_FFM', 'BIA-BIA_FFFI', 'BIA-BIA_FMI', 'BIA-BIA_Fat', 'BIA-BIA_Frame_num', 'BIA-BIA_ICW', 'BIA-BIA_LDM', 'BIA-BIA_LST', 'BIA-BIA_SMM', 'BIA-BIA_TBW', 'PAQ_A-Season', 'PAQ_A-PAQ_A_Total', 'PAQ_C-Season', 'PAQ_C-PAQ_C_Total', 'PCIAT-PCIAT_Total', 'SDS-Season', 'SDS-SDS_Total_Raw', 'SDS-SDS_Total_T', 'PreInt_EduHx-Season', 'PreInt_EduHx-computerinternet_hoursday', 'sii', 'Age_Group', 'PCIAT_Cluster', 'CGAS-CGAS_Score_x_SDS-SDS_Total_Raw', 'CGAS-CGAS_Score_x_Physical-BMI'],
dtype='object')

Remaining columns after MICE imputation: Index(['id', 'Basic_Demos-Enroll_Season', 'Basic_Demos-Age', 'Basic_Demos-Sex', 'CGAS-Season', 'CGAS-CGAS_Score', 'Physical-Season', 'Physical-BMI', 'Physical-Height', 'Physical-Weight', 'Physical-Waist_Circumference', 'Physical-Diastolic_BP', 'Physical-HeartRate', 'Physical-Systolic_BP', 'Fitness_Endurance-Season', 'Fitness_Endurance-Max_Stage', 'Fitness_Endurance-Time_Mins', 'Fitness_Endurance-Time_Sec', 'FGC-Season', 'FGC-FGC CU', 'FGC-FGC CU_Zone', 'FGC-FGC GSND', 'FGC-FGC GSND_Zone', 'FGC-FGC GSD', 'FGC-FGC GSD_Zone', 'FGC-FGC PU', 'FGC-FGC PU_Zone', 'FGC-FGC SRL', 'FGC-FGC SRL_Zone', 'FGC-FGC SRR', 'FGC-FGC SRR_Zone', 'FGC-FGC TL', 'FGC-FGC TL_Zone', 'BIA-Season', 'BIA-BIA_Activity_Level_num', 'BIA-BIA_BMC', 'BIA-BIA_BMI', 'BIA-BIA_BMR', 'BIA-BIA_DEE', 'BIA-BIA_ECW', 'BIA-BIA_FFM', 'BIA-BIA_FFFI', 'BIA-BIA_FMI', 'BIA-BIA_Fat', 'BIA-BIA_Frame_num', 'BIA-BIA_ICW', 'BIA-BIA_LDM', 'BIA-BIA_LST', 'BIA-BIA_SMM', 'BIA-BIA_TBW', 'PAQ_A-Season', 'PAQ_A-PAQ_A_Total', 'PAQ_C-Season', 'PAQ_C-PAQ_C_Total', 'PCIAT-PCIAT_Total', 'SDS-Season'],
dtype='object')

```

'SDS-SDS_Total_Raw', 'SDS-SDS_Total_T', 'PreInt_EduHx-Season',
'PreInt_EduHx-computerinternet_hoursday', 'sii', 'Age_Group',
'PCIAT_Cluster', 'CGAS-CGAS_Score_x_SDS-SDS_Total_Raw',
'CGAS-CGAS_Score_x_Physical-BMI'],
dtype='object')
Categorical features identified: Index(['id', 'Basic_Demos-Enroll_Season',
'CGAS-Season', 'Physical-Season',
'Fitness_Endurance-Season', 'FGC-Season', 'BIA-Season', 'PAQ_A-Season',
'PAQ_C-Season', 'SDS-Season', 'PreInt_EduHx-Season', 'Age_Group'],
dtype='object')
Features to be included in VIF analysis: Index(['id', 'Basic_Demos-
Enroll_Season', 'Basic_Demos-Age', 'Basic_Demos-Sex',
'CGAS-Season', 'CGAS-CGAS_Score', 'Physical-Season', 'Physical-BMI',
'Physical-Height', 'Physical-Weight', 'Physical-Waist_Circumference',
'Physical-Diastolic_BP', 'Physical-HeartRate', 'Physical-Systolic_BP',
'Fitness_Endurance-Season', 'Fitness_Endurance-Max_Stage',
'Fitness_Endurance-Time_Mins', 'Fitness_Endurance-Time_Sec',
'FGC-Season', 'FGC-FGC CU', 'FGC-FGC CU_Zone', 'FGC-FGC GSND',
'FGC-FGC GSND_Zone', 'FGC-FGC GSD', 'FGC-FGC GSD_Zone', 'FGC-FGC PU',
'FGC-FGC PU_Zone', 'FGC-FGC SRL', 'FGC-FGC SRL_Zone', 'FGC-FGC SRR',
'FGC-FGC SRR_Zone', 'FGC-FGC TL', 'FGC-FGC TL_Zone', 'BIA-Season',
'BIA-BIA_Activity_Level_num', 'BIA-BIA_BMC', 'BIA-BIA_BMI',
'BIA-BIA_BMR', 'BIA-BIA_DEE', 'BIA-BIA_ECW', 'BIA-BIA_FFM',
'BIA-BIA_FFM', 'BIA-BIA_FMI', 'BIA-BIA_Fat', 'BIA-BIA_Frame_num',
'BIA-BIA_ICW', 'BIA-BIA_LDM', 'BIA-BIA_LST', 'BIA-BIA_SMM',
'BIA-BIA_TBW', 'PAQ_A-Season', 'PAQ_A-PAQ_A_Total', 'PAQ_C-Season',
'PAQ_C-PAQ_C_Total', 'PCIAT-PCIAT_Total', 'SDS-Season',
'SDS-SDS_Total_Raw', 'SDS-SDS_Total_T', 'PreInt_EduHx-Season',
'PreInt_EduHx-computerinternet_hoursday', 'sii', 'Age_Group',
'PCIAT_Cluster', 'CGAS-CGAS_Score_x_SDS-SDS_Total_Raw',
'CGAS-CGAS_Score_x_Physical-BMI'],
dtype='object')

```

VIF values for features:

		Feature	VIF
0		id	3.316759e+02
1	Basic_Demos-Enroll_Season		1.022143e+03
2		Basic_Demos-Age	1.780492e+07
3		Basic_Demos-Sex	6.257103e+03
4		CGAS-Season	6.162885e+02
..	
60		sii	5.279081e+04
61		Age_Group	2.949623e+01
62		PCIAT_Cluster	5.652697e+05
63	CGAS-CGAS_Score_x_SDS-SDS_Total_Raw		4.602746e+07
64	CGAS-CGAS_Score_x_Physical-BMI		1.825490e+08

[65 rows x 2 columns]

Features marked for removal due to high VIF: ['id', 'Basic_Demos-Enroll_Season',

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'Basic_Demos-Age', 'Basic_Demos-Sex', 'CGAS-Season', 'CGAS-CGAS_Score',
'Physical-Season', 'Physical-BMI', 'Physical-Height', 'Physical-Weight',
'Physical-Waist_Circumference', 'Physical-Diastolic_BP', 'Physical-HeartRate',
'Physical-Systolic_BP', 'Fitness_Endurance-Season', 'Fitness_Endurance-
Max_Stage', 'Fitness_Endurance-Time_Mins', 'Fitness_Endurance-Time_Sec', 'FGC-
Season', 'FGC-FGC CU', 'FGC-FGC CU_Zone', 'FGC-FGC GSND', 'FGC-FGC GSND_Zone',
'FGC-FGC_GSD', 'FGC-FGC_GSD_Zone', 'FGC-FGC PU', 'FGC-FGC PU_Zone', 'FGC-
FGC_SRL', 'FGC-FGC_SRL_Zone', 'FGC-FGC_SRR', 'FGC-FGC_SRR_Zone', 'FGC-FGC_TL',
'FGC-FGC_TL_Zone', 'BIA-Season', 'BIA-BIA_Activity_Level_num', 'BIA-BIA_BMC',
'BIA-BIA_BMI', 'BIA-BIA_BMR', 'BIA-BIA_DEE', 'BIA-BIA_ECW', 'BIA-BIA_FFM', 'BIA-
BIA_FFFMI', 'BIA-BIA_FMI', 'BIA-BIA_Fat', 'BIA-BIA_Frame_num', 'BIA-BIA_ICW',
'BIA-BIA_LDM', 'BIA-BIA_LST', 'BIA-BIA_SMM', 'BIA-BIA_TBW', 'PAQ_A-Season',
'PAQ_A-PAQ_A_Total', 'PAQ_C-Season', 'PAQ_C-PAQ_C_Total', 'PCIAT-PCIAT_Total',
'SDS-Season', 'SDS-SDS_Total_Raw', 'SDS-SDS_Total_T', 'PreInt_EduHx-Season',
'PreInt_EduHx-computerinternet_hoursday', 'sii', 'Age_Group', 'PCIAT_Cluster',
'CGAS-CGAS_Score_x_SDS-SDS_Total_Raw', 'CGAS-CGAS_Score_x_Physical-BMI']

```

Warning: Attempting to remove too many features. Adjusting VIF threshold to retain features.

Remaining columns after removing high VIF features: Index(['id', 'Basic_Demos-Enroll_Season', 'Basic_Demos-Age', 'Basic_Demos-Sex',

```

'CGAS-Season', 'CGAS-CGAS_Score', 'Physical-Season', 'Physical-BMI',
'Physical-Height', 'Physical-Weight', 'Physical-Waist_Circumference',
'Physical-Diastolic_BP', 'Physical-HeartRate', 'Physical-Systolic_BP',
'Fitness_Endurance-Season', 'Fitness_Endurance-Max_Stage',
'Fitness_Endurance-Time_Mins', 'Fitness_Endurance-Time_Sec',
'FGC-Season', 'FGC-FGC CU', 'FGC-FGC CU_Zone', 'FGC-FGC GSND',
'FGC-FGC GSND_Zone', 'FGC-FGC_GSD', 'FGC-FGC_GSD_Zone', 'FGC-FGC PU',
'FGC-FGC PU_Zone', 'FGC-FGC_SRL', 'FGC-FGC_SRL_Zone', 'FGC-FGC_SRR',
'FGC-FGC_SRR_Zone', 'FGC-FGC_TL', 'FGC-FGC_TL_Zone', 'BIA-Season',
'BIA-BIA_Activity_Level_num', 'BIA-BIA_BMC', 'BIA-BIA_BMI',
'BIA-BIA_BMR', 'BIA-BIA_DEE', 'BIA-BIA_ECW', 'BIA-BIA_FFM',
'BIA-BIA_FFFMI', 'BIA-BIA_FMI', 'BIA-BIA_Fat', 'BIA-BIA_Frame_num',
'BIA-BIA_ICW', 'BIA-BIA_LDM', 'BIA-BIA_LST', 'BIA-BIA_SMM',
'BIA-BIA_TBW', 'PAQ_A-Season', 'PAQ_A-PAQ_A_Total', 'PAQ_C-Season',
'PAQ_C-PAQ_C_Total', 'PCIAT-PCIAT_Total', 'SDS-Season',
'SDS-SDS_Total_Raw', 'SDS-SDS_Total_T', 'PreInt_EduHx-Season',
'PreInt_EduHx-computerinternet_hoursday', 'sii', 'Age_Group',
'PCIAT_Cluster', 'CGAS-CGAS_Score_x_SDS-SDS_Total_Raw',
'CGAS-CGAS_Score_x_Physical-BMI'],
dtype='object')

```

Remaining columns after creating missingness indicators: Index(['id',

```

'Basic_Demos-Enroll_Season', 'Basic_Demos-Age', 'Basic_Demos-Sex',
'CGAS-Season', 'CGAS-CGAS_Score', 'Physical-Season', 'Physical-BMI',
'Physical-Height', 'Physical-Weight', 'Physical-Waist_Circumference',
'Physical-Diastolic_BP', 'Physical-HeartRate', 'Physical-Systolic_BP',
'Fitness_Endurance-Season', 'Fitness_Endurance-Max_Stage',
'Fitness_Endurance-Time_Mins', 'Fitness_Endurance-Time_Sec',
'FGC-Season', 'FGC-FGC CU', 'FGC-FGC CU_Zone', 'FGC-FGC GSND',

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```

'FGC-FGC_GSND_Zone', 'FGC-FGC_GSD', 'FGC-FGC_GSD_Zone', 'FGC-FGC_PU',
'FGC-FGC_PU_Zone', 'FGC-FGC_SRL', 'FGC-FGC_SRL_Zone', 'FGC-FGC_SRR',
'FGC-FGC_SRR_Zone', 'FGC-FGC_TL', 'FGC-FGC_TL_Zone', 'BIA-Season',
'BIA-BIA_Activity_Level_num', 'BIA-BIA_BMC', 'BIA-BIA_BMI',
'BIA-BIA_BMR', 'BIA-BIA_DEE', 'BIA-BIA_ECW', 'BIA-BIA_FFM',
'BIA-BIA_FFM', 'BIA-BIA_FMI', 'BIA-BIA_Fat', 'BIA-BIA_Frame_num',
'BIA-BIA_ICW', 'BIA-BIA_LDM', 'BIA-BIA_LST', 'BIA-BIA_SMM',
'BIA-BIA_TBW', 'PAQ_A-Season', 'PAQ_A-PAQ_A_Total', 'PAQ_C-Season',
'PAQ_C-PAQ_C_Total', 'PCIAT-PCIAT_Total', 'SDS-Season',
'SDS-SDS_Total_Raw', 'SDS-SDS_Total_T', 'PreInt_EduHx-Season',
'PreInt_EduHx-computerinternet_hoursday', 'sii', 'Age_Group',
'PCIAT_Cluster', 'CGAS-CGAS_Score_x_SDS-SDS_Total_Raw',
'CGAS-CGAS_Score_x_Physical-BMI'],
dtype='object')

```

Correlation of remaining interaction terms with PCIAT-PCIAT_Total:

CGAS-CGAS_Score_x_SDS-SDS_Total_Raw: 0.1211

CGAS-CGAS_Score_x_Physical-BMI: 0.1258

Correlation of remaining interaction terms with sii:

CGAS-CGAS_Score_x_SDS-SDS_Total_Raw: 0.1052

CGAS-CGAS_Score_x_Physical-BMI: 0.1120

Correlation of remaining interaction terms with PCIAT_Cluster:

CGAS-CGAS_Score_x_SDS-SDS_Total_Raw: 0.0326

CGAS-CGAS_Score_x_Physical-BMI: 0.0758

[26]: train_df.head()

	id	Basic_Demos-Enroll_Season	Basic_Demos-Age	Basic_Demos-Sex	\
0	0.709955	0.559547	5.0	0.0	
2	0.449738	0.543858	10.0	1.0	
3	0.579846	0.598983	9.0	0.0	
5	0.579846	0.475815	13.0	1.0	
11	0.449738	0.559547	11.0	0.0	
	CGAS-Season	CGAS-CGAS_Score	Physical-Season	Physical-BMI	\
0	0.527092	51.0	0.526350	16.877316	
2	0.538294	71.0	0.526350	16.648696	
3	0.538294	71.0	0.516702	18.292347	
5	0.527092	50.0	0.516702	22.279952	
11	0.515994	66.0	0.471466	18.269958	
	Physical-Height	Physical-Weight	Physical-Waist_Circumference	\	
0	46.000000	50.800000	23.154724		
2	56.500000	75.600000	25.755813		
3	56.000000	81.600000	30.237799		

5	59.500000	112.200000	33.812417			
11	55.568097	83.565122	26.013867			
	Physical-Diastolic_BP	Physical-HeartRate	Physical-Systolic_BP	\		
0	69.273255	86.942701	111.584992			
2	65.000000	94.000000	117.000000			
3	60.000000	97.000000	117.000000			
5	60.000000	73.000000	102.000000			
11	69.317251	84.110761	116.626216			
	Fitness_Endurance-Season	Fitness_Endurance-Max_Stage	\			
0	0.562024	4.661823				
2	0.416561	5.000000				
3	0.419733	6.000000				
5	0.562024	3.781508				
11	0.562024	4.861046				
	Fitness_Endurance-Time_Mins	Fitness_Endurance-Time_Sec	FGC-Season	\		
0	5.902407	30.190591	0.539792			
2	7.000000	33.000000	0.539792			
3	9.000000	37.000000	0.531007			
5	6.496836	24.040340	0.531007			
11	8.019364	28.006224	0.552717			
	FGC-FGC CU	FGC-FGC CU_Zone	FGC-FGC GSND	FGC-FGC GSND_Zone	FGC-FGC GSD	\
0	0.000000	0.000000	12.457159	1.861092	7.105427	
2	20.000000	1.000000	10.200000	1.000000	14.700000	
3	18.000000	1.000000	15.489000	1.797822	17.595300	
5	12.000000	0.000000	16.500000	2.000000	17.900000	
11	10.701686	0.455832	19.270922	1.683190	19.325191	
	FGC-FGC GSD_Zone	FGC-FGC PU	FGC-FGC PU_Zone	FGC-FGC SRL	\	
0	2.104217	0.000000	0.000000	7.000000		
2	2.000000	7.000000	1.000000	10.000000		
3	2.176744	5.000000	0.000000	7.000000		
5	2.000000	6.000000	0.000000	10.000000		
11	1.630797	5.096538	0.302039	8.751021		
	FGC-FGC SRL_Zone	FGC-FGC SRR	FGC-FGC SRR_Zone	FGC-FGC TL	\	
0	0.00000	6.00000	0.000000	6.000000		
2	1.00000	10.00000	1.000000	5.000000		
3	0.00000	7.00000	0.000000	7.000000		
5	1.00000	11.00000	1.000000	8.000000		
11	0.68659	8.92129	0.690292	9.021283		
	FGC-FGC TL_Zone	BIA-Season	BIA-BIA_Activity_Level_num	BIA-BIA_BMC	\	
0	1.000000	0.534475	2.000000	2.668550		

2	0.000000	0.490251	2.658187	7.660622		
3	1.000000	0.566098	3.000000	3.841910		
5	0.000000	0.566098	2.000000	4.330360		
11	0.723361	0.490251	2.517398	7.660620		
0	BIA-BIA_BMI	BIA-BIA_BMR	BIA-BIA_DEE	BIA-BIA_ECW	BIA-BIA_FFM	\
0	16.879200	932.498000	1492.000000	8.255980	41.586200	
2	18.540298	1229.028902	2004.524112	20.415826	73.170824	
3	18.294300	1131.430000	1923.440000	15.592500	62.775700	
5	30.186500	1330.970000	1996.450000	30.212400	84.028500	
11	18.540307	1229.029934	2020.016337	20.415797	73.170847	
0	BIA-BIA_FFCI	BIA-BIA_FMI	BIA-BIA_Fat	BIA-BIA_Frame_num	BIA-BIA_ICW	\
0	13.817700	3.061430	9.213770	1.000000	24.434900	
2	14.810861	3.729442	5.294715	1.531391	32.829003	
3	14.074000	4.220330	18.824300	2.000000	30.404100	
5	16.687700	13.498800	67.971500	2.000000	32.914100	
11	14.810861	3.729442	10.512782	1.644971	32.829002	
0	BIA-BIA_LDM	BIA-BIA_LST	BIA-BIA_SMM	BIA-BIA_TBW	PAQ_A-Season	\
0	8.895360	38.917700	19.541300	32.690900	0.480263	
2	19.926022	65.510201	42.760486	53.244807	0.480263	
3	16.779000	58.933800	26.479800	45.996600	0.480263	
5	20.902000	79.698200	35.380400	63.126500	0.480263	
11	19.926031	65.510206	29.831805	53.244809	0.480263	
0	PAQ_A-PAQ_A_Total	PAQ_C-Season	PAQ_C-PAQ_C_Total	PCIAT-PCIAT_Total	\	
0	1.773888	0.460443	2.68491	55.0		
2	1.991617	0.544231	2.17000	28.0		
3	1.978289	0.716160	2.45100	44.0		
5	1.968692	0.579612	4.11000	34.0		
11	2.110197	0.716160	1.10000	10.0		
0	SDS-Season	SDS-SDS_Total_Raw	SDS-SDS_Total_T	PreInt_EduHx-Season	\	
0	0.467407	42.186222	59.348885	0.564223		
2	0.515460	38.000000	54.000000	0.534033		
3	0.512539	31.000000	45.000000	0.602178		
5	0.512539	40.000000	56.000000	0.486120		
11	0.611293	42.000000	59.000000	0.564223		
0	PreInt_EduHx-computerinternet_hoursday	sii	Age_Group	PCIAT_Cluster	\	
0		3.0	2.0	0.443345	5.0	
2		2.0	0.0	0.362030	7.0	
3		0.0	1.0	0.362030	4.0	
5		0.0	1.0	0.855589	3.0	
11		0.0	0.0	0.855589	3.0	

	CGAS-CGAS_Score_x_SDS-SDS_Total_Raw	CGAS-CGAS_Score_x_Physical-BMI
0	2156.462944	860.743100
2	2698.000000	1182.057420
3	2201.000000	1298.756633
5	2000.000000	1113.997599
11	2772.000000	1206.032260

Actigraphy Data analysis

```
[27]: import pyarrow.parquet as pq

# Load one of the series data files
series_file = 'kaggle/input/child-mind-institute-problematic-internet-use/
              ↪series_train.parquet/id=0745c390/part-0.parquet'
series_data = pq.read_table(series_file).to_pandas()

# Display the first few rows of the series data
print("Sample Series Data:")
display(series_data.head())
```

Sample Series Data:

	step	X	Y	Z	enmo	anglez	non-wear_flag	\
0	0	0.088385	-0.021719	0.988333	0.000192	84.628494	0.0	
1	1	0.088750	-0.021823	0.988698	0.000246	84.657318	0.0	
2	2	0.022700	-0.015929	0.988151	0.023109	87.189415	0.0	
3	3	-0.076641	-0.048411	0.932135	0.043126	85.428131	0.0	
4	4	0.006432	0.036354	1.000651	0.006071	88.175079	0.0	

	light	battery_voltage	time_of_day	weekday	quarter	\
0	8.250000	4186.000000	5220000000000000	6	2	
1	15.666667	4185.166504	5220500000000000	6	2	
2	13.583333	4187.000000	5438500000000000	6	2	
3	11.500000	4187.000000	5439000000000000	6	2	
4	1.661765	4187.000000	5439500000000000	6	2	

	relative_date_PCIAT
0	15.0
1	15.0
2	15.0
3	15.0
4	15.0

```
[28]: series_data.shape
```

```
[28]: (50458, 13)
```

```
[29]: #import pandas as pd
#import os
#path_arr_train = []
#path_arr_test = []
#for dirname, _, filenames in os.walk('kaggle/input'):
#    for filename in filenames:
#        path = os.path.join(dirname, filename)
#        if('series_train.parquet' in path):
#            path_arr_train.append(path)
#        if('series_test.parquet' in path):
#            path_arr_test.append(path)

#print(len(path_arr_train)/2)
#dataframes = []
#for i in range(int(len(path_arr_train)/2)):
#    file = path_arr_train[i]
#    df = pd.read_parquet(file)
#    dataframes.append(df)
#print("Train Dataframe Generated")
#actigraphy_train_df = pd.concat(dataframes)

import pandas as pd
import os

# Initialize empty lists to hold the paths for train and test data
path_arr_train = []
path_arr_test = []

# Traverse the input directory to find and store paths of the parquet files
print("Here1")
for dirname, _, filenames in os.walk('kaggle/input'):
    for filename in filenames:
        path = os.path.join(dirname, filename)
        if 'series_train.parquet' in path:
            path_arr_train.append(path)
        if 'series_test.parquet' in path:
            path_arr_test.append(path)

# List to hold individual dataframes
print('Here2')
dataframes = []

# Loop through each train file path
for file in path_arr_train:
    # Read the dataframe from parquet file
    df = pd.read_parquet(file)
```

```

# Extract the ID from the file path. Assuming that the ID is always after "id=" in the path.
# For example: /kaggle/input/child-mind-institute-problematic-internet-use/series_train.parquet/id=5f099188/part-0.parquet
id_value = file.split('id=')[1].split('/')[0] # Extracts "5f099188" from the path

# Add the ID as a new column to the dataframe
df['ID'] = id_value

# Append the dataframe to the list
dataframes.append(df)

print("Train Dataframe Generated")

# Concatenate all the individual dataframes into a single dataframe
actigraphy_train_df = pd.concat(dataframes)

# Display the first few rows of the combined dataframe
print(actigraphy_train_df.head())

```

Here1

Here2

Train Dataframe Generated

	step	X	Y	Z	enmo	anglez	non-wear_flag	\
0	0	-0.853643	-0.452480	-0.004268	0.039495	-2.348142	0.0	
1	1	-0.740500	-0.481082	-0.096710	0.076673	-6.455178	0.0	
2	2	-0.602861	0.028234	0.374689	0.052310	31.838375	0.0	
3	3	-0.008948	0.018434	1.001781	0.002765	88.850754	0.0	
4	4	-0.007265	0.017022	1.001847	0.002946	88.973587	0.0	

	light	battery_voltage	time_of_day	weekday	quarter	\
0	3.00	4171.000000	5232000000000000	5	2	
1	21.00	4171.083496	5232500000000000	5	2	
2	21.00	4171.166504	5233000000000000	5	2	
3	18.50	4171.250000	5233500000000000	5	2	
4	18.75	4171.333496	5234000000000000	5	2	

	relative_date_PCIAT	ID
0	-25.0	af485add
1	-25.0	af485add
2	-25.0	af485add
3	-25.0	af485add
4	-25.0	af485add

[30]: dataframes = []
for file in path_arr_test:

```

# Read the dataframe from parquet file
df = pd.read_parquet(file)

# Extract the ID from the file path. Assuming that the ID is always after
# "id=" in the path.
# For example: /kaggle/input/child-mind-institute-problematic-internet-use/
# series_train.parquet/id=5f099188/part-0.parquet
id_value = file.split('id=')[1].split('/')[0] # Extracts "5f099188" from
# the path

# Add the ID as a new column to the dataframe
df['ID'] = id_value

# Append the dataframe to the list
dataframes.append(df)

actigraphy_test_df = pd.concat(dataframes)

```

[31]: actigraphy_test_df.columns

[31]: Index(['step', 'X', 'Y', 'Z', 'enmo', 'anglez', 'non-wear_flag', 'light',
 'battery_voltage', 'time_of_day', 'weekday', 'quarter',
 'relative_date_PCIAT', 'ID'],
 dtype='object')

[32]: actigraphy_train_df.head()

	step	X	Y	Z	enmo	anglez	non-wear_flag	light	battery_voltage	time_of_day	weekday	quarter	relative_date_PCIAT	ID
0	0	-0.853643	-0.452480	-0.004268	0.039495	-2.348142	0.0							
1	1	-0.740500	-0.481082	-0.096710	0.076673	-6.455178	0.0							
2	2	-0.602861	0.028234	0.374689	0.052310	31.838375	0.0							
3	3	-0.008948	0.018434	1.001781	0.002765	88.850754	0.0							
4	4	-0.007265	0.017022	1.001847	0.002946	88.973587	0.0							
0	3.00	4171.000000	5232000000000000			5	2							
1	21.00	4171.083496	5232500000000000			5	2							
2	21.00	4171.166504	5233000000000000			5	2							
3	18.50	4171.250000	5233500000000000			5	2							
4	18.75	4171.333496	5234000000000000			5	2							

```
[33]: actigraphy_train_df['ID'].value_counts()
```

```
[33]: ID
2a88cbe9    756212
0b4014f0    727484
697c41d7    674410
75b0446f    594911
04cb2c30    593331
...
055156e2    2080
b802aec3    1940
a8b0428d    1386
f8ff0bc8    1195
e1ea8dd7    927
Name: count, Length: 996, dtype: int64
```

```
[34]: # List to hold individual dataframes for test data
test_dataframes = []
```

```
# Loop through each test file path
for file in path_arr_test:
    # Read the dataframe from parquet file
    df = pd.read_parquet(file)

    # Extract the ID from the file path. Assuming that the ID is always after ↵ "id=" in the path.
    # For example: /kaggle/input/child-mind-institute-problematic-internet-use/ ↵ series_test.parquet/id=5f099188/part-0.parquet
    id_value = file.split('id=')[1].split('/')[0] # Extracts "5f099188" from ↵ the path

    # Add the ID as a new column to the dataframe
    df['ID'] = id_value

    # Append the dataframe to the list
    test_dataframes.append(df)

print("Test Dataframe Generated")

# Concatenate all the individual test dataframes into a single dataframe
actigraphy_test_df = pd.concat(test_dataframes)

# Display the first few rows of the combined test dataframe
print(actigraphy_test_df.head())
```

Test Dataframe Generated

	step	X	Y	Z	enmo	anglez	non-wear_flag	\
0	0	0.021536	0.022214	-1.022370	0.022853	-88.280762	0.0	

```
1      1  0.022005  0.022187 -1.019740  0.020231 -88.241707      0.0
2      2  0.022240  0.022005 -1.019401  0.019893 -88.170067      0.0
3      3  0.021589  0.022578 -1.018177  0.018667 -88.250031      0.0
4      4  0.022005  0.023763 -1.014323  0.016848 -88.130775      0.0
```

```
    light  battery_voltage   time_of_day  weekday  quarter \
0  53.000000      4188.000000  5694000000000000      4      3
1  51.666668      4188.166504  5694500000000000      4      3
2  50.333332      4188.333496  5695000000000000      4      3
3  50.500000      4188.500000  5695500000000000      4      3
4  33.166668      4181.000000  5723500000000000      4      3
```

```
relative_date_PCIAT          ID
0                  41.0  00115b9f
1                  41.0  00115b9f
2                  41.0  00115b9f
3                  41.0  00115b9f
4                  41.0  00115b9f
```

```
[35]: actigraphy_test_df.head()
```

```
[35]: step          X          Y          Z        enmo      anglez  non-wear_flag \
0      0  0.021536  0.022214 -1.022370  0.022853 -88.280762      0.0
1      1  0.022005  0.022187 -1.019740  0.020231 -88.241707      0.0
2      2  0.022240  0.022005 -1.019401  0.019893 -88.170067      0.0
3      3  0.021589  0.022578 -1.018177  0.018667 -88.250031      0.0
4      4  0.022005  0.023763 -1.014323  0.016848 -88.130775      0.0
```

```
    light  battery_voltage   time_of_day  weekday  quarter \
0  53.000000      4188.000000  5694000000000000      4      3
1  51.666668      4188.166504  5694500000000000      4      3
2  50.333332      4188.333496  5695000000000000      4      3
3  50.500000      4188.500000  5695500000000000      4      3
4  33.166668      4181.000000  5723500000000000      4      3
```

```
relative_date_PCIAT          ID
0                  41.0  00115b9f
1                  41.0  00115b9f
2                  41.0  00115b9f
3                  41.0  00115b9f
4                  41.0  00115b9f
```

```
[36]: # Install necessary package
#!pip install pyts
```

```
# Import required libraries
#import pandas as pd
#from pyts.decomposition import SingularSpectrumAnalysis
```

```

# Create a copy of the dataframe to store denoised columns
#denoised_actigraphy_df = actigraphy_train_df.copy()

# Columns to apply SSA denoising on
#columns_to_denoise = ['X', 'Y', 'Z']

# Apply SSA to each of the specified columns using pyts
#for column in columns_to_denoise:
#    # Get the column series
#    series = actigraphy_train_df[column]
#
#    # Set window_size dynamically based on the length of the series
#    series_length = len(series)
#    window_size = min(10, series_length - 1) # Set to minimum value
#
#    # Create an SSA object if the window_size is valid
#    if window_size > 1:
#        ssa = SingularSpectrumAnalysis(window_size=window_size)
#
#        # Reshape series for SSA and apply fit_transform
#        denoised_series = ssa.fit_transform(series.values.reshape(1, -1))[0]
#
#        # Store the denoised series back to the dataframe
#        denoised_actigraphy_df[column] = denoised_series
#
#    # Display the denoised dataframe head
#denoised_actigraphy_df.head()

```

Aggregating Actigraphy Data To get started, we can first implement the aggregation step and verify the results before moving to the next step:

```
[37]: # Aggregate actigraphy data by ID
actigraphy_train_summary_df = (
    actigraphy_train_df
    .groupby('ID') # Group by ID
    .agg({
        'X': ['mean', 'std', 'min', 'max'], # Aggregate X with mean, std, min, max
        'Y': ['mean', 'std', 'min', 'max'], # Aggregate Y with mean, std, min, max
        'Z': ['mean', 'std', 'min', 'max'], # Aggregate Z with mean, std, min, max
        'enmo': ['mean', 'std'], # Aggregate enmo with mean, std
        'anglez': ['mean', 'std'], # Aggregate anglez with mean, std
        'non-wear_flag': 'mean', # Proportion of non-wear time
        'light': ['mean', 'std'], # Aggregate light with mean, std
    })
)
```

```

        'battery_voltage': ['mean', 'std'], # Aggregate battery voltage
        'time_of_day': 'mean', # Mean time of day
        'weekday': 'mean', # Average weekday for the activity readings
        'quarter': 'mean', # Average quarter for the activity readings
        'relative_date_PCIAT': 'mean' # Average relative date PCIAT
    })
)

# Flatten MultiIndex columns
actigraphy_train_summary_df.columns = ['_'.join(col) for col in [
    actigraphy_train_summary_df.columns
]]

# Reset index to make 'ID' a column again
actigraphy_train_summary_df.reset_index(inplace=True)

# Display first few rows of the aggregated summary
actigraphy_train_summary_df.head()

```

[37]:

	ID	X_mean	X_std	X_min	X_max	Y_mean	Y_std	\
0	00115b9f	-0.316384	0.453665	-1.746094	1.507865	0.016009	0.502702	
1	001f3379	-0.004272	0.351545	-1.038711	1.034351	0.016859	0.303812	
2	00f332d1	0.208036	0.486977	-1.952594	1.666465	0.057094	0.443755	
3	01085eb3	-0.343396	0.516126	-2.284304	1.000692	-0.055826	0.424303	
4	012cadd8	0.018670	0.595251	-2.143912	3.341210	0.071660	0.508311	
		Y_min	Y_max	Z_mean	Z_std	Z_min	Z_max	enmo_mean \
0	-2.905339	1.666354	-0.167890	0.585710	-1.048372	1.546979	0.047388	
1	-1.522690	1.946303	-0.631731	0.623476	-1.018787	1.146284	0.011926	
2	-2.361866	1.016429	0.141550	0.683114	-1.016758	2.239939	0.030255	
3	-2.276082	1.011419	-0.254433	0.564593	-1.022549	1.299293	0.032946	
4	-3.373025	4.442658	-0.061682	0.578022	-1.003249	2.321265	0.058280	
		enmo_std	anglez_mean	anglez_std	non-wear_flag_mean	light_mean	\	
0	0.106351	-10.580416	42.947170		0.000000	42.296310		
1	0.024331	-55.630768	50.303635		0.655708	16.771980		
2	0.104136	6.687339	52.754208		0.171246	66.563393		
3	0.083798	-17.589037	39.895645		0.035210	17.800735		
4	0.197285	-5.059758	39.994808		0.000000	54.893402		
		light_std	battery_voltage_mean	battery_voltage_std	time_of_day_mean	\		
0	208.168976		4053.578857		112.404037	5.046215e+13		
1	95.327438		3838.189453		155.573868	4.321212e+13		
2	286.916595		3848.583252		166.968582	4.318680e+13		
3	73.023468		3849.650146		171.100159	4.338433e+13		
4	230.972397		3974.910889		119.525154	4.343573e+13		
		weekday_mean	quarter_mean	relative_date_PCIAT_mean				

0	4.470182	3.0	53.201683
1	3.909848	3.0	79.435593
2	3.832677	2.0	26.152903
3	3.963284	4.0	49.910686
4	4.168412	4.0	-1.168288

Computing and Adding Fourier Transforms Here's how we can incorporate Fourier Transforms in the aggregated actigraphy data:

```
[38]: import numpy as np

# Function to compute top n Fourier coefficients
def compute_top_n_fourier_coefficients(signal, n=5):
    # Perform the Fourier Transform on the signal
    fft_coeffs = np.fft.fft(signal)
    # Calculate magnitudes of the FFT coefficients
    magnitudes = np.abs(fft_coeffs)
    # Get top n coefficients based on magnitudes (excluding the DC component at index 0)
    top_n_indices = np.argsort(magnitudes)[-n:]
    # Return the real and imaginary parts of the top n coefficients
    top_n_real_parts = fft_coeffs[top_n_indices].real
    top_n_imag_parts = fft_coeffs[top_n_indices].imag
    return top_n_real_parts, top_n_imag_parts

# List to store Fourier features for each participant
fourier_features_list = []

# Calculate Fourier Transforms for each ID in the actigraphy training data
for participant_id, participant_data in actigraphy_train_df.groupby('ID'):
    # Calculate Fourier coefficients for each axis
    fourier_X_real, fourier_X_imag = compute_top_n_fourier_coefficients(participant_data['X'].values)
    fourier_Y_real, fourier_Y_imag = compute_top_n_fourier_coefficients(participant_data['Y'].values)
    fourier_Z_real, fourier_Z_imag = compute_top_n_fourier_coefficients(participant_data['Z'].values)

    # Create a dictionary to store Fourier features for this participant
    fourier_features = {
        'ID': participant_id,
        'fourier_X_real': fourier_X_real.mean(),  # Using mean of the top real parts as a feature
        'fourier_X_imag': fourier_X_imag.mean(),  # Using mean of the top imaginary parts as a feature
        'fourier_Y_real': fourier_Y_real.mean(),
        'fourier_Y_imag': fourier_Y_imag.mean(),
    }
```

```

        'fourier_Z_real': fourier_Z_real.mean(),
        'fourier_Z_imag': fourier_Z_imag.mean(),
    }
fourier_features_list.append(fourier_features)

# Convert the list of Fourier features into a DataFrame
fourier_features_df = pd.DataFrame(fourier_features_list)

# Merge the Fourier features into the existing actigraphy summary dataframe
actigraphy_train_summary_with_fourier_df = pd.merge(
    actigraphy_train_summary_df,
    fourier_features_df,
    on='ID',
    how='left'
)

# Display first few rows of the combined summary
print(actigraphy_train_summary_with_fourier_df.head())

```

	ID	X_mean	X_std	X_min	X_max	Y_mean	Y_std	\	
0	00115b9f	-0.316384	0.453665	-1.746094	1.507865	0.016009	0.502702		
1	001f3379	-0.004272	0.351545	-1.038711	1.034351	0.016859	0.303812		
2	00f332d1	0.208036	0.486977	-1.952594	1.666465	0.057094	0.443755		
3	01085eb3	-0.343396	0.516126	-2.284304	1.000692	-0.055826	0.424303		
4	012cadd8	0.018670	0.595251	-2.143912	3.341210	0.071660	0.508311		
		Y_min	Y_max	Z_mean	Z_std	Z_min	Z_max	enmo_mean	\
0	-2.905339	1.666354	-0.167890	0.585710	-1.048372	1.546979	0.047388		
1	-1.522690	1.946303	-0.631731	0.623476	-1.018787	1.146284	0.011926		
2	-2.361866	1.016429	0.141550	0.683114	-1.016758	2.239939	0.030255		
3	-2.276082	1.011419	-0.254433	0.564593	-1.022549	1.299293	0.032946		
4	-3.373025	4.442658	-0.061682	0.578022	-1.003249	2.321265	0.058280		
		enmo_std	anglez_mean	anglez_std	non-wear_flag_mean	light_mean	\		
0	0.106351	-10.580416	42.947170		0.000000	42.296310			
1	0.024331	-55.630768	50.303635		0.655708	16.771980			
2	0.104136	6.687339	52.754208		0.171246	66.563393			
3	0.083798	-17.589037	39.895645		0.035210	17.800735			
4	0.197285	-5.059758	39.994808		0.000000	54.893402			
		light_std	battery_voltage_mean	battery_voltage_std	time_of_day_mean	\			
0	208.168976		4053.578857		112.404037	5.046215e+13			
1	95.327438		3838.189453		155.573868	4.321212e+13			
2	286.916595		3848.583252		166.968582	4.318680e+13			
3	73.023468		3849.650146		171.100159	4.338433e+13			
4	230.972397		3974.910889		119.525154	4.343573e+13			
		weekday_mean	quarter_mean	relative_date_PCIAT_mean	fourier_X_real	\			

```

0      4.470182          3.0          53.201683 -2653.531675
1      3.909848          3.0          79.435593  4103.865122
2      3.832677          2.0          26.152903  14903.301506
3      3.963284          4.0          49.910686 -25796.646158
4      4.168412          4.0          -1.168288  6637.890207

fourier_X_imag  fourier_Y_real  fourier_Y_imag  fourier_Z_real \
0   -1.083578e-14    705.803060  -2.074467e+02   1995.401835
1   -1.680035e+03   14385.071425  3.120931e+03  -26765.674436
2   -3.637979e-13   -923.242685  7.275958e-13  -5261.764351
3   -1.093525e-12  -10776.376135  -1.989520e-13 -8614.531458
4    5.618541e+02   2279.335449  -3.637979e-13 -4597.967535

fourier_Z_imag
0   -5.684342e-15
1   -8.731149e-12
2    7.275958e-13
3   -9.563905e-13
4    0.000000e+00

```

```
[39]: pd.set_option('display.max_columns', None)
actigraphy_train_summary_with_fourier_df.head()
```

```

[39]:      ID     X_mean     X_std     X_min     X_max     Y_mean     Y_std \
0  00115b9f -0.316384  0.453665 -1.746094  1.507865  0.016009  0.502702
1  001f3379 -0.004272  0.351545 -1.038711  1.034351  0.016859  0.303812
2  00f332d1  0.208036  0.486977 -1.952594  1.666465  0.057094  0.443755
3  01085eb3 -0.343396  0.516126 -2.284304  1.000692 -0.055826  0.424303
4  012cadd8  0.018670  0.595251 -2.143912  3.341210  0.071660  0.508311

      Y_min     Y_max     Z_mean     Z_std     Z_min     Z_max enmo_mean \
0 -2.905339  1.666354 -0.167890  0.585710 -1.048372  1.546979  0.047388
1 -1.522690  1.946303 -0.631731  0.623476 -1.018787  1.146284  0.011926
2 -2.361866  1.016429  0.141550  0.683114 -1.016758  2.239939  0.030255
3 -2.276082  1.011419 -0.254433  0.564593 -1.022549  1.299293  0.032946
4 -3.373025  4.442658 -0.061682  0.578022 -1.003249  2.321265  0.058280

enmo_std anglez_mean anglez_std non-wear_flag_mean light_mean \
0  0.106351 -10.580416  42.947170           0.000000  42.296310
1  0.024331 -55.630768  50.303635           0.655708  16.771980
2  0.104136   6.687339  52.754208           0.171246  66.563393
3  0.083798 -17.589037  39.895645           0.035210  17.800735
4  0.197285 -5.059758  39.994808           0.000000  54.893402

light_std battery_voltage_mean battery_voltage_std time_of_day_mean \
0  208.168976           4053.578857          112.404037  5.046215e+13
1   95.327438           3838.189453          155.573868  4.321212e+13

```

```

2 286.916595          3848.583252          166.968582          4.318680e+13
3 73.023468           3849.650146          171.100159          4.338433e+13
4 230.972397          3974.910889          119.525154          4.343573e+13

    weekday_mean   quarter_mean  relative_date_PCIAT_mean  fourier_X_real \
0      4.470182           3.0                  53.201683       -2653.531675
1      3.909848           3.0                  79.435593        4103.865122
2      3.832677           2.0                  26.152903       14903.301506
3      3.963284           4.0                  49.910686      -25796.646158
4      4.168412           4.0                 -1.168288       6637.890207

    fourier_X_imag  fourier_Y_real  fourier_Y_imag  fourier_Z_real \
0     -1.083578e-14      705.803060      -2.074467e+02      1995.401835
1     -1.680035e+03     14385.071425      3.120931e+03      -26765.674436
2     -3.637979e-13      -923.242685      7.275958e-13      -5261.764351
3     -1.093525e-12     -10776.376135      -1.989520e-13      -8614.531458
4      5.618541e+02      2279.335449      -3.637979e-13      -4597.967535

    fourier_Z_imag
0     -5.684342e-15
1     -8.731149e-12
2      7.275958e-13
3     -9.563905e-13
4      0.000000e+00

```

Explanation Function compute_top_n_fourier_coefficients: Calculates the top n Fourier coefficients (real and imaginary parts) for a given time-series signal. Loop through each participant's data: For each ID, compute the Fourier Transform of X, Y, and Z columns. Feature Extraction: Extract relevant Fourier features (mean real and imaginary parts of top coefficients). Merging: Combine these Fourier features with the existing summary statistics for a more comprehensive dataset.

Time Domain Features

```
[40]: # Function to calculate day and night activity based on time_of_day
def calculate_day_night_activity(df, day_start=6, day_end=18):
    # Calculate day activity (time_of_day between day_start and day_end)
    day_activity = df[(df['time_of_day'] >= day_start) & (df['time_of_day'] <=
    ↪day_end)]['enmo'].sum()
    # Calculate night activity (time_of_day outside the day range)
    night_activity = df[(df['time_of_day'] < day_start) | (df['time_of_day'] >=
    ↪day_end)]['enmo'].sum()
    return day_activity, night_activity

# List to store time-domain features for each participant
time_features_list = []

# Calculate time-domain features for each participant
```

```

for participant_id, participant_data in actigraphy_train_df.groupby('ID'):
    # Calculate day and night activity
    day_activity, night_activity =_
    calculate_day_night_activity(participant_data)
    activity_ratio_day_night = day_activity / (night_activity + 1e-6)  # Avoid_
    ↵division by zero

    # Calculate proportion of non-wear time
    non_wear_proportion = participant_data['non-wear_flag'].mean()

    # Calculate proportion of time spent in different activity levels based on_
    ↵'enmo'
    sedentary_time = participant_data[participant_data['enmo'] < 0.05].shape[0]
    light_activity_time = participant_data[(participant_data['enmo'] >= 0.05) &_
    ↵(participant_data['enmo'] < 0.5)].shape[0]
    moderate_activity_time = participant_data[(participant_data['enmo'] >= 0.5) &_
    ↵(participant_data['enmo'] < 1)].shape[0]
    vigorous_activity_time = participant_data[participant_data['enmo'] >= 1]._
    ↵shape[0]
    total_time = participant_data.shape[0]

    # Calculate proportions
    sedentary_proportion = sedentary_time / total_time
    light_activity_proportion = light_activity_time / total_time
    moderate_activity_proportion = moderate_activity_time / total_time
    vigorous_activity_proportion = vigorous_activity_time / total_time

    # Create a dictionary of time domain features
    time_features = {
        'ID': participant_id,
        'activity_during_day': day_activity,
        'activity_during_night': night_activity,
        'activity_ratio_day_night': activity_ratio_day_night,
        'non_wear_proportion': non_wear_proportion,
        'sedentary_proportion': sedentary_proportion,
        'light_activity_proportion': light_activity_proportion,
        'moderate_activity_proportion': moderate_activity_proportion,
        'vigorous_activity_proportion': vigorous_activity_proportion
    }
    time_features_list.append(time_features)

# Convert the list of time domain features into a DataFrame
time_features_df = pd.DataFrame(time_features_list)

# Merge the time-domain features into the actigraphy summary with Fourier_
    ↵features

```

```

actigraphy_combined_features_df = pd.merge(
    actigraphy_train_summary_with_fourier_df, # The dataframe with Fourier
    ↵features
    time_features_df, # The new time-domain features
    on='ID',
    how='left'
)

# Display the first few rows of the final combined feature set
actigraphy_combined_features_df.head()

```

[40]:

	ID	X_mean	X_std	X_min	X_max	Y_mean	Y_std	\
0	00115b9f	-0.316384	0.453665	-1.746094	1.507865	0.016009	0.502702	
1	001f3379	-0.004272	0.351545	-1.038711	1.034351	0.016859	0.303812	
2	00f332d1	0.208036	0.486977	-1.952594	1.666465	0.057094	0.443755	
3	01085eb3	-0.343396	0.516126	-2.284304	1.000692	-0.055826	0.424303	
4	012cadd8	0.018670	0.595251	-2.143912	3.341210	0.071660	0.508311	
	Y_min	Y_max	Z_mean	Z_std	Z_min	Z_max	enmo_mean	\
0	-2.905339	1.666354	-0.167890	0.585710	-1.048372	1.546979	0.047388	
1	-1.522690	1.946303	-0.631731	0.623476	-1.018787	1.146284	0.011926	
2	-2.361866	1.016429	0.141550	0.683114	-1.016758	2.239939	0.030255	
3	-2.276082	1.011419	-0.254433	0.564593	-1.022549	1.299293	0.032946	
4	-3.373025	4.442658	-0.061682	0.578022	-1.003249	2.321265	0.058280	
	enmo_std	anglez_mean	anglez_std	non-wear_flag_mean	light_mean	\		
0	0.106351	-10.580416	42.947170		0.000000	42.296310		
1	0.024331	-55.630768	50.303635		0.655708	16.771980		
2	0.104136	6.687339	52.754208		0.171246	66.563393		
3	0.083798	-17.589037	39.895645		0.035210	17.800735		
4	0.197285	-5.059758	39.994808		0.000000	54.893402		
	light_std	battery_voltage_mean	battery_voltage_std	time_of_day_mean	\			
0	208.168976	4053.578857		112.404037	5.046215e+13			
1	95.327438	3838.189453		155.573868	4.321212e+13			
2	286.916595	3848.583252		166.968582	4.318680e+13			
3	73.023468	3849.650146		171.100159	4.338433e+13			
4	230.972397	3974.910889		119.525154	4.343573e+13			
	weekday_mean	quarter_mean	relative_date_PCIAT_mean	fourier_X_real	\			
0	4.470182	3.0		53.201683	-2653.531675			
1	3.909848	3.0		79.435593	4103.865122			
2	3.832677	2.0		26.152903	14903.301506			
3	3.963284	4.0		49.910686	-25796.646158			
4	4.168412	4.0		-1.168288	6637.890207			
	fourier_X_imag	fourier_Y_real	fourier_Y_imag	fourier_Z_real	\			

```

0   -1.083578e-14      705.803060    -2.074467e+02      1995.401835
1   -1.680035e+03      14385.071425    3.120931e+03     -26765.674436
2   -3.637979e-13      -923.242685    7.275958e-13     -5261.764351
3   -1.093525e-12      -10776.376135   -1.989520e-13     -8614.531458
4   5.618541e+02       2279.335449    -3.637979e-13     -4597.967535

fourier_Z_imag activity_during_day activity_during_night \
0   -5.684342e-15      0.0          2053.305176
1   -8.731149e-12      0.0          4727.518555
2   7.275958e-13       0.0          12537.293945
3   -9.563905e-13      0.0          12221.464844
4   0.000000e+00       0.0          5655.915527

activity_ratio_day_night non_wear_proportion sedentary_proportion \
0           0.0          0.000000      0.792453
1           0.0          0.655708      0.978501
2           0.0          0.171246      0.867572
3           0.0          0.035210      0.840178
4           0.0          0.000000      0.789187

light_activity_proportion moderate_activity_proportion \
0           0.198131      0.007870
1           0.021171      0.000288
2           0.124059      0.005562
3           0.154229      0.004567
4           0.189535      0.012808

vigorous_activity_proportion
0           0.001546
1           0.000040
2           0.002807
3           0.001027
4           0.008470

```

Time Domain Feature Engineering

Activity During Day and Night

Create two new features: `activity_during_day` and `activity_during_night`, based on `time_of_day`. If `time_of_day` falls within a specific range (e.g., 6 AM to 6 PM for day and 6 PM to 6 AM for night), sum up the activity values in `enmo` for each period. Activity Ratio (Day/Night)

Calculate the ratio of activity during the day to activity during the night: `activity_ratio_day_night` = `activity_during_day` / (`activity_during_night` + 1e-6). This helps measure how active a participant is during the day compared to the night. Proportion of Non-Wear Time

Use the `non-wear_flag` column to calculate the proportion of time each participant was not wearing the device: `non_wear_proportion` = `non_wear_time` / `total_time`. Activity Level Classification

Create thresholds for `enmo` values to classify activity levels (e.g., sedentary, light activity, moderate

activity, vigorous activity). Calculate the proportion of time spent in each activity level. Additional Domain-Specific Features

Use columns like anglez, light, and battery_voltage to derive additional features if they show any correlation with the target variable sii

Merge the DataFrames Let's merge actigraphy_combined_features_df with the main training dataset based on the ID column to ensure we have a single DataFrame for the combined analysis.

```
[41]: train_df['id'] = ID_arr
```

```
[42]: # Merging the main training dataset with actigraphy_combined_features_df based on the ID column
merged_train_df = pd.merge(train_df, actigraphy_combined_features_df, how='left', left_on='id', right_on='ID')

# Dropping the redundant ID column from actigraphy_combined_features_df if needed
merged_train_df = merged_train_df.drop(columns=['ID'])

# Display the first few rows of the merged DataFrame to confirm the merge
#print(merged_train_df.head())
```

```
[43]: merged_train_df.head()
```

```
[43]:      id  Basic_Demos-Enroll_Season  Basic_Demos-Age  Basic_Demos-Sex \
0  00008ff9                  0.559547          5.0            0.0
1  00105258                  0.543858         10.0            1.0
2  00115b9f                  0.598983          9.0            0.0
3  001f3379                  0.475815         13.0            1.0
4  00abe655                  0.559547         11.0            0.0

      CGAS-Season  CGAS-CGAS_Score  Physical-Season  Physical-BMI \
0        0.527092         51.0          0.526350       16.877316
1        0.538294         71.0          0.526350       16.648696
2        0.538294         71.0          0.516702       18.292347
3        0.527092         50.0          0.516702       22.279952
4        0.515994         66.0          0.471466       18.269958

      Physical-Height  Physical-Weight  Physical-Waist_Circumference \
0        46.000000      50.800000                  23.154724
1        56.500000      75.600000                  25.755813
2        56.000000      81.600000                  30.237799
3        59.500000     112.200000                  33.812417
4        55.568097      83.565122                  26.013867

      Physical-Diastolic_BP  Physical-HeartRate  Physical-Systolic_BP \

```

0	69.273255	86.942701	111.584992		
1	65.000000	94.000000	117.000000		
2	60.000000	97.000000	117.000000		
3	60.000000	73.000000	102.000000		
4	69.317251	84.110761	116.626216		
Fitness_Endurance-Season \ Fitness_Endurance-Max_Stage \					
0	0.562024	4.661823			
1	0.416561	5.000000			
2	0.419733	6.000000			
3	0.562024	3.781508			
4	0.562024	4.861046			
Fitness_Endurance-Time_Mins \ Fitness_Endurance-Time_Sec \ FGC-Season \					
0	5.902407	30.190591	0.539792		
1	7.000000	33.000000	0.539792		
2	9.000000	37.000000	0.531007		
3	6.496836	24.040340	0.531007		
4	8.019364	28.006224	0.552717		
FGC-FGC CU \ FGC-FGC CU_Zone \ FGC-FGC GSND \ FGC-FGC GSND_Zone \ FGC-FGC GSD \					
0	0.000000	0.000000	12.457159	1.861092	7.105427
1	20.000000	1.000000	10.200000	1.000000	14.700000
2	18.000000	1.000000	15.489000	1.797822	17.595300
3	12.000000	0.000000	16.500000	2.000000	17.900000
4	10.701686	0.455832	19.270922	1.683190	19.325191
FGC-FGC GSD_Zone \ FGC-FGC PU \ FGC-FGC PU_Zone \ FGC-FGC SRL \					
0	2.104217	0.000000	0.000000	7.000000	
1	2.000000	7.000000	1.000000	10.000000	
2	2.176744	5.000000	0.000000	7.000000	
3	2.000000	6.000000	0.000000	10.000000	
4	1.630797	5.096538	0.302039	8.751021	
FGC-FGC SRL_Zone \ FGC-FGC SRR \ FGC-FGC SRR_Zone \ FGC-FGC TL \					
0	0.00000	6.00000	0.000000	6.000000	
1	1.00000	10.00000	1.000000	5.000000	
2	0.00000	7.00000	0.000000	7.000000	
3	1.00000	11.00000	1.000000	8.000000	
4	0.68659	8.92129	0.690292	9.021283	
FGC-FGC TL_Zone \ BIA-Season \ BIA-BIA_Activity_Level_num \ BIA-BIA_BMC \					
0	1.000000	0.534475	2.000000	2.668550	
1	0.000000	0.490251	2.658187	7.660622	
2	1.000000	0.566098	3.000000	3.841910	
3	0.000000	0.566098	2.000000	4.330360	
4	0.723361	0.490251	2.517398	7.660620	

	BIA-BIA_BMI	BIA-BIA_BMR	BIA-BIA_DEE	BIA-BIA_ECW	BIA-BIA_FFM	\
0	16.879200	932.498000	1492.000000	8.255980	41.586200	
1	18.540298	1229.028902	2004.524112	20.415826	73.170824	
2	18.294300	1131.430000	1923.440000	15.592500	62.775700	
3	30.186500	1330.970000	1996.450000	30.212400	84.028500	
4	18.540307	1229.029934	2020.016337	20.415797	73.170847	
	BIA-BIA_FFM	BIA-BIA_FMI	BIA-BIA_Fat	BIA-BIA_Frame_num	BIA-BIA_ICW	\
0	13.817700	3.061430	9.213770	1.000000	24.434900	
1	14.810861	3.729442	5.294715	1.531391	32.829003	
2	14.074000	4.220330	18.824300	2.000000	30.404100	
3	16.687700	13.498800	67.971500	2.000000	32.914100	
4	14.810861	3.729442	10.512782	1.644971	32.829002	
	BIA-BIA_LDM	BIA-BIA_LST	BIA-BIA_SMM	BIA-BIA_TBW	PAQ_A-Season	\
0	8.895360	38.917700	19.541300	32.690900	0.480263	
1	19.926022	65.510201	42.760486	53.244807	0.480263	
2	16.779000	58.933800	26.479800	45.996600	0.480263	
3	20.902000	79.698200	35.380400	63.126500	0.480263	
4	19.926031	65.510206	29.831805	53.244809	0.480263	
	PAQ_A-PAQ_A_Total	PAQ_C-Season	PAQ_C-PAQ_C_Total	PCIAT-PCIAT_Total	\	
0	1.773888	0.460443	2.68491	55.0		
1	1.991617	0.544231	2.17000	28.0		
2	1.978289	0.716160	2.45100	44.0		
3	1.968692	0.579612	4.11000	34.0		
4	2.110197	0.716160	1.10000	10.0		
	SDS-Season	SDS-SDS_Total_Raw	SDS-SDS_Total_T	PreInt_EduHx-Season	\	
0	0.467407	42.186222	59.348885	0.564223		
1	0.515460	38.000000	54.000000	0.534033		
2	0.512539	31.000000	45.000000	0.602178		
3	0.512539	40.000000	56.000000	0.486120		
4	0.611293	42.000000	59.000000	0.564223		
	PreInt_EduHx-computerinternet_hoursday	ssi	Age_Group	PCIAT_Cluster	\	
0		3.0	2.0	0.443345	5.0	
1		2.0	0.0	0.362030	7.0	
2		0.0	1.0	0.362030	4.0	
3		0.0	1.0	0.855589	3.0	
4		0.0	0.0	0.855589	3.0	
	CGAS-CGAS_Score_x_SDs-SDs_Total_Raw	CGAS-CGAS_Score_x_Physical-BMI	\			
0	2156.462944	860.743100				
1	2698.000000	1182.057420				
2	2201.000000	1298.756633				

3		2000.000000		1113.997599				
4		2772.000000		1206.032260				
	X_mean	X_std	X_min	X_max	Y_mean	Y_std	Y_min	\
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
2	-0.316384	0.453665	-1.746094	1.507865	0.016009	0.502702	-2.905339	
3	-0.004272	0.351545	-1.038711	1.034351	0.016859	0.303812	-1.522690	
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
	Y_max	Z_mean	Z_std	Z_min	Z_max	enmo_mean	enmo_std	\
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
2	1.666354	-0.167890	0.585710	-1.048372	1.546979	0.047388	0.106351	
3	1.946303	-0.631731	0.623476	-1.018787	1.146284	0.011926	0.024331	
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
	anglez_mean	anglez_std	non-wear_flag_mean	light_mean	light_std			\
0	NaN	NaN		NaN	NaN		NaN	
1	NaN	NaN		NaN	NaN		NaN	
2	-10.580416	42.947170		0.000000	42.29631	208.168976		
3	-55.630768	50.303635		0.655708	16.77198	95.327438		
4	NaN	NaN		NaN	NaN		NaN	
	battery_voltage_mean	battery_voltage_std	time_of_day_mean	weekday_mean				\
0		NaN		NaN				
1		NaN		NaN				
2		4053.578857		112.404037		5.046215e+13		4.470182
3		3838.189453		155.573868		4.321212e+13		3.909848
4		NaN		NaN		NaN		NaN
	quarter_mean	relative_date_PCIAT_mean	fourier_X_real	fourier_X_imag				\
0	NaN		NaN	NaN				
1	NaN		NaN	NaN				
2	3.0		53.201683	-2653.531675		-1.083578e-14		
3	3.0		79.435593	4103.865122		-1.680035e+03		
4	NaN		NaN	NaN				
	fourier_Y_real	fourier_Y_imag	fourier_Z_real	fourier_Z_imag				\
0	NaN		NaN	NaN				
1	NaN		NaN	NaN				
2	705.803060	-207.446683	1995.401835	-5.684342e-15				
3	14385.071425	3120.930726	-26765.674436	-8.731149e-12				
4	NaN		NaN	NaN				
	activity_during_day	activity_during_night	activity_ratio_day_night					\
0		NaN		NaN				

1	NaN	NaN	NaN
2	0.0	2053.305176	0.0
3	0.0	4727.518555	0.0
4	NaN	NaN	NaN
	non_wear_proportion	sedentary_proportion	light_activity_proportion \
0	NaN	NaN	NaN
1	NaN	NaN	NaN
2	0.000000	0.792453	0.198131
3	0.655708	0.978501	0.021171
4	NaN	NaN	NaN
	moderate_activity_proportion	vigorous_activity_proportion	
0	NaN	NaN	
1	NaN	NaN	
2	0.007870	0.001546	
3	0.000288	0.000040	
4	NaN	NaN	

```
[44]: # Define the list of actigraphy feature columns
actigraphy_columns = [
    'X_mean', 'X_std', 'X_min', 'X_max', 'Y_mean', 'Y_std', 'Y_min', 'Y_max',
    'Z_mean', 'Z_std', 'Z_min', 'Z_max', 'enmo_mean', 'enmo_std', 'anglez_mean',
    'anglez_std', 'non-wear_flag_mean', 'light_mean', 'light_std', ↴
    ↵'battery_voltage_mean',
    'battery_voltage_std', 'time_of_day_mean', 'weekday_mean', 'quarter_mean',
    'relative_date_PCIAT_mean', 'fourier_X_real', 'fourier_X_imag', ↴
    ↵'fourier_Y_real',
    'fourier_Y_imag', 'fourier_Z_real', 'fourier_Z_imag', 'activity_during_day',
    'activity_during_night', 'activity_ratio_day_night', 'non_wear_proportion',
    'sedentary_proportion', 'light_activity_proportion', ↴
    ↵'moderate_activity_proportion',
    'vigorous_activity_proportion'
]

# Fill NaN values in actigraphy columns with zeros if all actigraphy columns ↴
# are NaN in a row
merged_train_df[actigraphy_columns] = merged_train_df[actigraphy_columns].
    ↴apply(lambda row: row.fillna(0) if row.isnull().all() else row, axis=1)

# Create actigraphy_present column
# If all actigraphy columns have 0 values for a given row, set ↴
# actigraphy_present to 0, otherwise 1
merged_train_df['actigraphy_present'] = merged_train_df[actigraphy_columns].
    ↴apply(lambda row: 0 if (row == 0).all() else 1, axis=1)
```

```
# Display the first few rows to verify the results
merged_train_df.head()
```

```
[44]:      id  Basic_Demos-Enroll_Season  Basic_Demos-Age  Basic_Demos-Sex \
0  00008ff9                  0.559547          5.0          0.0
1  00105258                  0.543858         10.0          1.0
2  00115b9f                  0.598983          9.0          0.0
3  001f3379                  0.475815         13.0          1.0
4  00abe655                  0.559547         11.0          0.0

      CGAS-Season  CGAS-CGAS_Score  Physical-Season  Physical-BMI \
0      0.527092        51.0       0.526350     16.877316
1      0.538294        71.0       0.526350     16.648696
2      0.538294        71.0       0.516702     18.292347
3      0.527092        50.0       0.516702     22.279952
4      0.515994        66.0       0.471466     18.269958

      Physical-Height  Physical-Weight  Physical-Waist_Circumference \
0      46.000000      50.800000            23.154724
1      56.500000      75.600000            25.755813
2      56.000000      81.600000            30.237799
3      59.500000     112.200000            33.812417
4      55.568097      83.565122            26.013867

      Physical-Diastolic_BP  Physical-HeartRate  Physical-Systolic_BP \
0      69.273255        86.942701        111.584992
1      65.000000        94.000000        117.000000
2      60.000000        97.000000        117.000000
3      60.000000        73.000000        102.000000
4      69.317251        84.110761        116.626216

      Fitness_Endurance-Season  Fitness_Endurance-Max_Stage \
0                  0.562024          4.661823
1                  0.416561          5.000000
2                  0.419733          6.000000
3                  0.562024          3.781508
4                  0.562024          4.861046

      Fitness_Endurance-Time_Mins  Fitness_Endurance-Time_Sec  FGC-Season \
0                  5.902407          30.190591        0.539792
1                  7.000000          33.000000        0.539792
2                  9.000000          37.000000        0.531007
3                 6.496836          24.040340        0.531007
4                 8.019364          28.006224        0.552717

      FGC-FGC CU  FGC-FGC CU_Zone  FGC-FGC GSND  FGC-FGC GSND_Zone  FGC-FGC GSD \
0      0.000000        0.000000      12.457159          1.861092        7.105427
```

1	20.000000	1.000000	10.200000	1.000000	14.700000	
2	18.000000	1.000000	15.489000	1.797822	17.595300	
3	12.000000	0.000000	16.500000	2.000000	17.900000	
4	10.701686	0.455832	19.270922	1.683190	19.325191	
	FGC-FGC_GSD_Zone	FGC-FGC_PU	FGC-FGC_PU_Zone	FGC-FGC_SRL	\	
0	2.104217	0.000000	0.000000	7.000000		
1	2.000000	7.000000	1.000000	10.000000		
2	2.176744	5.000000	0.000000	7.000000		
3	2.000000	6.000000	0.000000	10.000000		
4	1.630797	5.096538	0.302039	8.751021		
	FGC-FGC_SRL_Zone	FGC-FGC_SRR	FGC-FGC_SRR_Zone	FGC-FGC_TL	\	
0	0.00000	6.00000	0.000000	6.000000		
1	1.00000	10.00000	1.000000	5.000000		
2	0.00000	7.00000	0.000000	7.000000		
3	1.00000	11.00000	1.000000	8.000000		
4	0.68659	8.92129	0.690292	9.021283		
	FGC-FGC_TL_Zone	BIA-Season	BIA-BIA_Activity_Level_num	BIA-BIA_BMC	\	
0	1.000000	0.534475		2.000000	2.668550	
1	0.000000	0.490251		2.658187	7.660622	
2	1.000000	0.566098		3.000000	3.841910	
3	0.000000	0.566098		2.000000	4.330360	
4	0.723361	0.490251		2.517398	7.660620	
	BIA-BIA_BMI	BIA-BIA_BMR	BIA-BIA_DEE	BIA-BIA_ECW	BIA-BIA_FFM	\
0	16.879200	932.498000	1492.000000	8.255980	41.586200	
1	18.540298	1229.028902	2004.524112	20.415826	73.170824	
2	18.294300	1131.430000	1923.440000	15.592500	62.775700	
3	30.186500	1330.970000	1996.450000	30.212400	84.028500	
4	18.540307	1229.029934	2020.016337	20.415797	73.170847	
	BIA-BIA_FFCI	BIA-BIA_FMI	BIA-BIA_Fat	BIA-BIA_Frame_num	BIA-BIA_ICW	\
0	13.817700	3.061430	9.213770	1.000000	24.434900	
1	14.810861	3.729442	5.294715	1.531391	32.829003	
2	14.074000	4.220330	18.824300	2.000000	30.404100	
3	16.687700	13.498800	67.971500	2.000000	32.914100	
4	14.810861	3.729442	10.512782	1.644971	32.829002	
	BIA-BIA_LDM	BIA-BIA_LST	BIA-BIA_SMM	BIA-BIA_TBW	PAQ_A-Season	\
0	8.895360	38.917700	19.541300	32.690900	0.480263	
1	19.926022	65.510201	42.760486	53.244807	0.480263	
2	16.779000	58.933800	26.479800	45.996600	0.480263	
3	20.902000	79.698200	35.380400	63.126500	0.480263	
4	19.926031	65.510206	29.831805	53.244809	0.480263	

	PAQ_A-PAQ_A_Total	PAQ_C-Season	PAQ_C-PAQ_C_Total	PCIAT-PCIAT_Total	\			
0	1.773888	0.460443	2.68491	55.0				
1	1.991617	0.544231	2.17000	28.0				
2	1.978289	0.716160	2.45100	44.0				
3	1.968692	0.579612	4.11000	34.0				
4	2.110197	0.716160	1.10000	10.0				
	SDS-Season	SDS-SDS_Total_Raw	SDS-SDS_Total_T	PreInt_EduHx-Season	\			
0	0.467407	42.186222	59.348885	0.564223				
1	0.515460	38.000000	54.000000	0.534033				
2	0.512539	31.000000	45.000000	0.602178				
3	0.512539	40.000000	56.000000	0.486120				
4	0.611293	42.000000	59.000000	0.564223				
	PreInt_EduHx-computerinternet_hoursday	sii	Age_Group	PCIAT_Cluster	\			
0		3.0	2.0	0.443345	5.0			
1		2.0	0.0	0.362030	7.0			
2		0.0	1.0	0.362030	4.0			
3		0.0	1.0	0.855589	3.0			
4		0.0	0.0	0.855589	3.0			
	CGAS-CGAS_Score_x_SDSDS_Total_Raw	CGAS-CGAS_Score_x_Physical-BMI	\					
0		2156.462944		860.743100				
1		2698.000000		1182.057420				
2		2201.000000		1298.756633				
3		2000.000000		1113.997599				
4		2772.000000		1206.032260				
	X_mean	X_std	X_min	X_max	Y_mean	Y_std	Y_min	\
0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2	-0.316384	0.453665	-1.746094	1.507865	0.016009	0.502702	-2.905339	
3	-0.004272	0.351545	-1.038711	1.034351	0.016859	0.303812	-1.522690	
4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
	Y_max	Z_mean	Z_std	Z_min	Z_max	enmo_mean	enmo_std	\
0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2	1.666354	-0.167890	0.585710	-1.048372	1.546979	0.047388	0.106351	
3	1.946303	-0.631731	0.623476	-1.018787	1.146284	0.011926	0.024331	
4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
	anglez_mean	anglez_std	non-wear_flag_mean	light_mean	light_std	\		
0	0.000000	0.000000		0.000000	0.000000	0.000000		
1	0.000000	0.000000		0.000000	0.000000	0.000000		
2	-10.580416	42.947170		0.000000	42.29631	208.168976		
3	-55.630768	50.303635		0.655708	16.77198	95.327438		

4	0.000000	0.000000	0.000000	0.000000	0.000000	
0	battery_voltage_mean	battery_voltage_std	time_of_day_mean	weekday_mean		\
1	0.000000	0.000000	0.000000e+00	0.000000		
2	0.000000	0.000000	0.000000e+00	0.000000		
3	4053.578857	112.404037	5.046215e+13	4.470182		
4	3838.189453	155.573868	4.321212e+13	3.909848		
	0.000000	0.000000	0.000000e+00	0.000000		
0	quarter_mean	relative_date_PCIAT_mean	fourier_X_real	fourier_X_imag		\
1	0.0	0.000000	0.000000	0.000000e+00		
2	0.0	0.000000	0.000000	0.000000e+00		
3	3.0	53.201683	-2653.531675	-1.083578e-14		
4	3.0	79.435593	4103.865122	-1.680035e+03		
	0.0	0.000000	0.000000	0.000000e+00		
0	fourier_Y_real	fourier_Y_imag	fourier_Z_real	fourier_Z_imag		\
1	0.000000	0.000000	0.000000	0.000000e+00		
2	0.000000	0.000000	0.000000	0.000000e+00		
3	705.803060	-207.446683	1995.401835	-5.684342e-15		
4	14385.071425	3120.930726	-26765.674436	-8.731149e-12		
	0.000000	0.000000	0.000000	0.000000e+00		
0	activity_during_day	activity_during_night	activity_ratio_day_night			\
1	0.0	0.000000	0.0			
2	0.0	0.000000	0.0			
3	0.0	2053.305176	0.0			
4	0.0	4727.518555	0.0			
	0.0	0.000000	0.0			
0	non_wear_proportion	sedentary_proportion	light_activity_proportion			\
1	0.000000	0.000000	0.000000			
2	0.000000	0.000000	0.000000			
3	0.655708	0.792453	0.198131			
4	0.000000	0.978501	0.021171			
	0.000000	0.000000	0.000000			
0	moderate_activity_proportion	vigorous_activity_proportion				\
1	0.000000	0.000000	0.000000			
2	0.007870	0.001546				
3	0.000288	0.000040				
4	0.000000	0.000000				
0	actigraphy_present					
1	0					

```
2          1
3          1
4          0
```

```
[45]: import matplotlib.pyplot as plt
import seaborn as sns

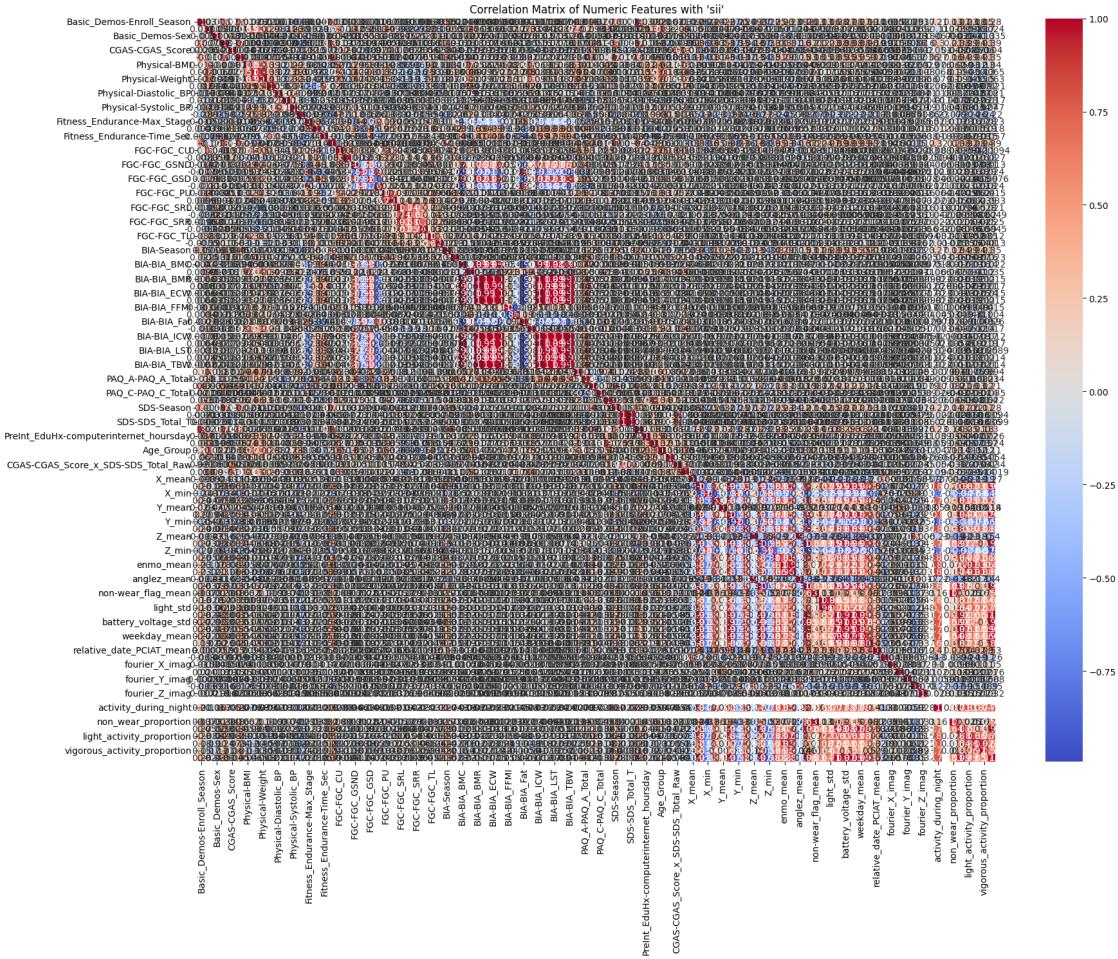
# Filter the merged DataFrame to include only numeric columns for the correlation matrix
numeric_df = merged_train_df.select_dtypes(include=[float, int])

# Display correlation matrix for the new features and sii
correlation_matrix = numeric_df.corr()
plt.figure(figsize=(20, 15))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title("Correlation Matrix of Numeric Features with 'sii'")
plt.show()

# Calculate basic statistics for actigraphy features grouped by 'sii'
grouped_stats = numeric_df.groupby(merged_train_df['sii']).agg(['mean', 'std', 'min', 'max'])
print(grouped_stats.head())

# Plot histograms or box plots for key features against 'sii'
key_features = ['X_mean', 'Y_mean', 'Z_mean', 'enmo_mean', 'non-wear_flag_mean',
                 'activity_ratio_day_night', 'sedentary_proportion',
                 'vigorous_activity_proportion']

for feature in key_features:
    if feature in numeric_df.columns: # Check if the feature is in the numeric DataFrame
        plt.figure(figsize=(10, 6))
        sns.boxplot(x='sii', y=feature, data=merged_train_df)
        plt.title(f'Distribution of {feature} by sii')
        plt.show()
```



Basic_Demos-Enroll_Season				Basic_Demos-Age				\	
	mean	std	min	max	mean	std			
sii									
-0.760696		0.598983	NaN	0.598983	0.598983			19.0	
-0.314713		0.475815	NaN	0.475815	0.475815			22.0	
-0.312714		0.559547	NaN	0.559547	0.559547			17.0	
-0.231091		0.598983	NaN	0.598983	0.598983			15.0	
-0.144216		0.475815	NaN	0.475815	0.475815			13.0	
Basic_Demos-Sex				CGAS-Season				\	
	std	min	max	mean	std	min	max	mean	
sii									
-0.760696	NaN	19.0	19.0	0.0	NaN	0.0	0.0	0.515994	NaN
-0.314713	NaN	22.0	22.0	1.0	NaN	1.0	1.0	0.515994	NaN
-0.312714	NaN	17.0	17.0	1.0	NaN	1.0	1.0	0.538294	NaN
-0.231091	NaN	15.0	15.0	0.0	NaN	0.0	0.0	0.538294	NaN
-0.144216	NaN	13.0	13.0	1.0	NaN	1.0	1.0	0.581124	NaN

CGAS-CGAS_Score								Physical-Season			\
	min	max		mean	std	min	max		mean		
sii											
-0.760696	0.515994	0.515994		58.0	NaN	58.0	58.0		0.601470		
-0.314713	0.515994	0.515994		75.0	NaN	75.0	75.0		0.523758		
-0.312714	0.538294	0.538294		76.0	NaN	76.0	76.0		0.516702		
-0.231091	0.538294	0.538294		60.0	NaN	60.0	60.0		0.526350		
-0.144216	0.581124	0.581124		72.0	NaN	72.0	72.0		0.516702		
 Physical-BMI											
	std	min	max	mean	std	min	max				\
sii											
-0.760696	NaN	0.601470	0.601470	23.840162	NaN	23.840162	23.840162				
-0.314713	NaN	0.523758	0.523758	26.056757	NaN	26.056757	26.056757				
-0.312714	NaN	0.516702	0.516702	29.789226	NaN	29.789226	29.789226				
-0.231091	NaN	0.526350	0.526350	16.864219	NaN	16.864219	16.864219				
-0.144216	NaN	0.516702	0.516702	17.455101	NaN	17.455101	17.455101				
 Physical-Height						Physical-Weight					
	mean	std	min	max		mean	std	min	max		\
sii											
-0.760696		72.0	NaN	72.0	72.0		175.8	NaN	175.8	175.8	
-0.314713		65.0	NaN	65.0	65.0		156.6	NaN	156.6	156.6	
-0.312714		67.0	NaN	67.0	67.0		190.2	NaN	190.2	190.2	
-0.231091		69.0	NaN	69.0	69.0		114.2	NaN	114.2	114.2	
-0.144216		68.0	NaN	68.0	68.0		114.8	NaN	114.8	114.8	
 Physical-Waist_Circumference						Physical-Diastolic_BP					
	mean	std	min	max		mean	std	min	max		\
sii											
-0.760696			36.0	NaN	36.0	36.0				71.0	
-0.314713			35.0	NaN	35.0	35.0				80.0	
-0.312714			34.0	NaN	34.0	34.0				63.0	
-0.231091			27.0	NaN	27.0	27.0				53.0	
-0.144216			27.0	NaN	27.0	27.0				80.0	
 Physical-HeartRate											
	std	min	max	mean	std	min	max				\
sii											
-0.760696	NaN	71.0	71.0		71.0	NaN	71.0	71.0			
-0.314713	NaN	80.0	80.0		78.0	NaN	78.0	78.0			
-0.312714	NaN	63.0	63.0		66.0	NaN	66.0	66.0			
-0.231091	NaN	53.0	53.0		93.0	NaN	93.0	93.0			
-0.144216	NaN	80.0	80.0		92.0	NaN	92.0	92.0			
 Physical-Systolic_BP						Fitness_Endurance-Season					
	mean	std	min	max		mean	std	min	max		\
sii											

-0.760696	135.0	NaN	135.0	135.0		0.562024	NaN
-0.314713	129.0	NaN	129.0	129.0		0.562024	NaN
-0.312714	108.0	NaN	108.0	108.0		0.562024	NaN
-0.231091	110.0	NaN	110.0	110.0		0.562024	NaN
-0.144216	127.0	NaN	127.0	127.0		0.562024	NaN

Fitness_Endurance-Max_Stage					\
	min	max	mean	std	min
sii					
-0.760696	0.562024	0.562024	4.435789	NaN	4.435789
-0.314713	0.562024	0.562024	4.198903	NaN	4.198903
-0.312714	0.562024	0.562024	5.799169	NaN	5.799169
-0.231091	0.562024	0.562024	5.240235	NaN	5.240235
-0.144216	0.562024	0.562024	5.430333	NaN	5.430333

Fitness_Endurance-Time_Mins					\
	max	mean	std	min	max
sii					
-0.760696	4.435789	7.143487	NaN	7.143487	7.143487
-0.314713	4.198903	6.624388	NaN	6.624388	6.624388
-0.312714	5.799169	4.528173	NaN	4.528173	4.528173
-0.231091	5.240235	7.535246	NaN	7.535246	7.535246
-0.144216	5.430333	7.165710	NaN	7.165710	7.165710

Fitness_Endurance-Time_Sec					FGC-Season	\
	mean	std	min	max	mean	std
sii						
-0.760696	20.126764	NaN	20.126764	20.126764	0.472214	NaN
-0.314713	29.121412	NaN	29.121412	29.121412	0.472214	NaN
-0.312714	29.726658	NaN	29.726658	29.726658	0.472214	NaN
-0.231091	25.809110	NaN	25.809110	25.809110	0.472214	NaN
-0.144216	22.464845	NaN	22.464845	22.464845	0.472214	NaN

FGC-FGC CU					\	
	min	max	mean	std	min	max
sii						
-0.760696	0.472214	0.472214	22.225245	NaN	22.225245	22.225245
-0.314713	0.472214	0.472214	23.222260	NaN	23.222260	23.222260
-0.312714	0.472214	0.472214	28.654766	NaN	28.654766	28.654766
-0.231091	0.472214	0.472214	24.285854	NaN	24.285854	24.285854
-0.144216	0.472214	0.472214	23.167038	NaN	23.167038	23.167038

FGC-FGC CU_Zone					FGC-FGC GSND	\	
	mean	std	min	max	mean	std	min
sii							
-0.760696	-0.035583	NaN	-0.035583	-0.035583	30.826376	NaN	30.826376
-0.314713	0.127326	NaN	0.127326	0.127326	30.610218	NaN	30.610218
-0.312714	0.202144	NaN	0.202144	0.202144	28.937106	NaN	28.937106

-0.231091	0.443701	NaN	0.443701	0.443701	24.795915	NaN	24.795915
-0.144216	0.614095	NaN	0.614095	0.614095	21.959201	NaN	21.959201

FGC-FGC_GSND_Zone						FGC-FGC_GSD \	
	max	mean	std	min	max	mean	
sii							
-0.760696	30.826376	1.258827	NaN	1.258827	1.258827	38.088400	
-0.314713	30.610218	1.490439	NaN	1.490439	1.490439	33.254582	
-0.312714	28.937106	2.084074	NaN	2.084074	2.084074	36.604509	
-0.231091	24.795915	1.790724	NaN	1.790724	1.790724	27.957054	
-0.144216	21.959201	2.129340	NaN	2.129340	2.129340	24.217935	

FGC-FGC_GSD_Zone						\	
	std	min	max	mean	std	min	max
sii							
-0.760696	NaN	38.088400	38.088400	1.921265	NaN	1.921265	1.921265
-0.314713	NaN	33.254582	33.254582	1.410570	NaN	1.410570	1.410570
-0.312714	NaN	36.604509	36.604509	3.872646	NaN	3.872646	3.872646
-0.231091	NaN	27.957054	27.957054	2.182940	NaN	2.182940	2.182940
-0.144216	NaN	24.217935	24.217935	2.889933	NaN	2.889933	2.889933

FGC-FGC_PU						FGC-FGC_PU_Zone \	
	mean	std	min	max	mean	std	min
sii							
-0.760696	13.365519	NaN	13.365519	13.365519	0.267869	NaN	0.267869
-0.314713	13.597431	NaN	13.597431	13.597431	0.482732	NaN	0.482732
-0.312714	15.138957	NaN	15.138957	15.138957	0.502361	NaN	0.502361
-0.231091	12.005235	NaN	12.005235	12.005235	0.472910	NaN	0.472910
-0.144216	10.818556	NaN	10.818556	10.818556	0.470968	NaN	0.470968

FGC-FGC_SRL						FGC-FGC_SRL_Zone \	
	max	mean	std	min	max	mean	std
sii							
-0.760696	0.267869	8.149241	NaN	8.149241	8.149241	0.650092	NaN
-0.314713	0.482732	9.043808	NaN	9.043808	9.043808	0.455634	NaN
-0.312714	0.502361	9.540310	NaN	9.540310	9.540310	0.757537	NaN
-0.231091	0.472910	8.610586	NaN	8.610586	8.610586	0.705078	NaN
-0.144216	0.470968	9.170370	NaN	9.170370	9.170370	0.661416	NaN

FGC-FGC_SRR						\	
	min	max	mean	std	min	max	
sii							
-0.760696	0.650092	0.650092	8.391354	NaN	8.391354	8.391354	
-0.314713	0.455634	0.455634	9.473053	NaN	9.473053	9.473053	
-0.312714	0.757537	0.757537	9.786045	NaN	9.786045	9.786045	
-0.231091	0.705078	0.705078	8.655687	NaN	8.655687	8.655687	
-0.144216	0.661416	0.661416	9.035880	NaN	9.035880	9.035880	

FGC-FGC_SRR_Zone							FGC-FGC_TL							\
	mean	std	min	max	mean	std	min		mean	std	min			
sii														
-0.760696	0.590861	NaN	0.590861	0.590861	10.102656	NaN	10.102656							
-0.314713	0.597148	NaN	0.597148	0.597148	10.514400	NaN	10.514400							
-0.312714	0.545723	NaN	0.545723	0.545723	9.906480	NaN	9.906480							
-0.231091	0.620721	NaN	0.620721	0.620721	10.413822	NaN	10.413822							
-0.144216	0.554199	NaN	0.554199	0.554199	10.305656	NaN	10.305656							
FGC-FGC_TL_Zone							BIA-Season							\
	max		mean	std	min		max		mean	std				
sii														
-0.760696	10.102656		0.497869	NaN	0.497869	0.497869	0.553902	NaN						
-0.314713	10.514400		0.493068	NaN	0.493068	0.493068	0.490251	NaN						
-0.312714	9.906480		0.547992	NaN	0.547992	0.547992	0.490251	NaN						
-0.231091	10.413822		0.658714	NaN	0.658714	0.658714	0.490251	NaN						
-0.144216	10.305656		0.763497	NaN	0.763497	0.763497	0.490251	NaN						
BIA-BIA_Activity_Level_num							BIA-BIA_BMC							\
	min		max				mean	std	min					
sii														
-0.760696	0.553902	0.553902					2.000000	NaN	2.000000					
-0.314713	0.490251	0.490251					3.115355	NaN	3.115355					
-0.312714	0.490251	0.490251					2.777763	NaN	2.777763					
-0.231091	0.490251	0.490251					2.762212	NaN	2.762212					
-0.144216	0.490251	0.490251					2.965925	NaN	2.965925					
BIA-BIA_BMC							BIA-BIA_BMI							\
	max		mean	std	min		max		mean	std				
sii														
-0.760696	2.000000	7.268830	NaN	7.268830	7.268830	23.842800	NaN							
-0.314713	3.115355	7.660618	NaN	7.660618	7.660618	18.540288	NaN							
-0.312714	2.777763	7.660596	NaN	7.660596	7.660596	18.540284	NaN							
-0.231091	2.762212	7.660639	NaN	7.660639	7.660639	18.540296	NaN							
-0.144216	2.965925	7.660641	NaN	7.660641	7.660641	18.540292	NaN							
BIA-BIA_BMR							BIA-BIA_DEE							\
	min		max		mean	std	min		max		mean	std		
sii														
-0.760696	23.842800	23.842800	1717.260000	NaN	1717.260000	1717.260000								
-0.314713	18.540288	18.540288	1229.031350	NaN	1229.031350	1229.031350								
-0.312714	18.540284	18.540284	1229.031514	NaN	1229.031514	1229.031514								
-0.231091	18.540296	18.540296	1229.029790	NaN	1229.029790	1229.029790								
-0.144216	18.540292	18.540292	1229.029818	NaN	1229.029818	1229.029818								
BIA-BIA_DEE							BIA-BIA_ECW							\
	mean	std	min		max		mean	std	min		mean	std		
sii														

-0.760696	2747.620000	NaN	2747.620000	2747.620000	37.770700	NaN
-0.314713	2113.409105	NaN	2113.409105	2113.409105	20.415860	NaN
-0.312714	2115.855098	NaN	2115.855098	2115.855098	20.415905	NaN
-0.231091	2098.439401	NaN	2098.439401	2098.439401	20.415835	NaN
-0.144216	2066.290026	NaN	2066.290026	2066.290026	20.415860	NaN

BIA-BIA_FFM						
	min	max	mean	std	min	max
sii						\
-0.760696	37.770700	37.770700	125.174000	NaN	125.174000	125.174000
-0.314713	20.415860	20.415860	73.170878	NaN	73.170878	73.170878
-0.312714	20.415905	20.415905	73.170890	NaN	73.170890	73.170890
-0.231091	20.415835	20.415835	73.170803	NaN	73.170803	73.170803
-0.144216	20.415860	20.415860	73.170800	NaN	73.170800	73.170800

BIA-BIA_FFFI				BIA-BIA_FMI				\
	mean	std	min	max	mean	std	min	\
sii								\
-0.760696	16.976700	NaN	16.976700	16.976700	6.866100	NaN	6.866100	
-0.314713	14.810860	NaN	14.810860	14.810860	3.729442	NaN	3.729442	
-0.312714	14.810854	NaN	14.810854	14.810854	3.729443	NaN	3.729443	
-0.231091	14.810860	NaN	14.810860	14.810860	3.729442	NaN	3.729442	
-0.144216	14.810860	NaN	14.810860	14.810860	3.729442	NaN	3.729442	

BIA-BIA_Fat				BIA-BIA_Frame_num				\
	max	mean	std	min	max		mean	\
sii								\
-0.760696	6.866100	50.625800	NaN	50.625800	50.625800		3.000000	
-0.314713	3.729442	71.754220	NaN	71.754220	71.754220		2.081289	
-0.312714	3.729443	96.382362	NaN	96.382362	96.382362		2.674607	
-0.231091	3.729442	41.429030	NaN	41.429030	41.429030		1.792602	
-0.144216	3.729442	41.112235	NaN	41.112235	41.112235		1.898075	

BIA-BIA_ICW				BIA-BIA_LDM				\
	std	min	max	mean	std	min	max	\
sii								\
-0.760696	NaN	3.000000	3.000000	53.428200	NaN	53.428200	53.428200	
-0.314713	NaN	2.081289	2.081289	32.828959	NaN	32.828959	32.828959	
-0.312714	NaN	2.674607	2.674607	32.828933	NaN	32.828933	32.828933	
-0.231091	NaN	1.792602	1.792602	32.828970	NaN	32.828970	32.828970	
-0.144216	NaN	1.898075	1.898075	32.828968	NaN	32.828968	32.828968	

BIA-BIA_LDM				BIA-BIA_LST				\
	mean	std	min	max	mean	std	min	\
sii								\
-0.760696	33.975300	NaN	33.975300	33.975300	117.905000	NaN	117.905000	
-0.314713	19.926104	NaN	19.926104	19.926104	65.510302	NaN	65.510302	
-0.312714	19.926159	NaN	19.926159	19.926159	65.510335	NaN	65.510335	

-0.231091	19.926087	NaN	19.926087	19.926087	65.510248	NaN	65.510248
-0.144216	19.926082	NaN	19.926082	19.926082	65.510251	NaN	65.510251

BIA-BIA_SMM						BIA-BIA_TBW						\
	max	mean	std	min	max	mean	std		max	mean	std	
sii												
-0.760696	117.905000	61.174600	NaN	61.174600	61.174600	91.198900	NaN					
-0.314713	65.510302	42.618569	NaN	42.618569	42.618569	53.244852	NaN					
-0.312714	65.510335	39.912373	NaN	39.912373	39.912373	53.244874	NaN					
-0.231091	65.510248	28.474838	NaN	28.474838	28.474838	53.244834	NaN					
-0.144216	65.510251	41.602053	NaN	41.602053	41.602053	53.244835	NaN					

PAQ_A-Season						\	
	min	max	mean	std	min	max	
sii							
-0.760696	91.198900	91.198900	0.480263	NaN	0.480263	0.480263	
-0.314713	53.244852	53.244852	0.480263	NaN	0.480263	0.480263	
-0.312714	53.244874	53.244874	1.017185	NaN	1.017185	1.017185	
-0.231091	53.244834	53.244834	1.017185	NaN	1.017185	1.017185	
-0.144216	53.244835	53.244835	0.938948	NaN	0.938948	0.938948	

PAQ_A-PAQ_A_Total						PAQ_C-Season	\
	mean	std	min	max	mean	std	
sii							
-0.760696	2.261004	NaN	2.261004	2.261004	0.460443	NaN	
-0.314713	2.212036	NaN	2.212036	2.212036	0.460443	NaN	
-0.312714	1.370000	NaN	1.370000	1.370000	0.460443	NaN	
-0.231091	1.820000	NaN	1.820000	1.820000	0.460443	NaN	
-0.144216	1.690000	NaN	1.690000	1.690000	0.460443	NaN	

PAQ_C-PAQ_C_Total						\	
	min	max	mean	std	min	max	
sii							
-0.760696	0.460443	0.460443	2.571950	NaN	2.571950	2.571950	
-0.314713	0.460443	0.460443	1.473492	NaN	1.473492	1.473492	
-0.312714	0.460443	0.460443	22.778263	NaN	22.778263	22.778263	
-0.231091	0.460443	0.460443	9.452195	NaN	9.452195	9.452195	
-0.144216	0.460443	0.460443	10.474885	NaN	10.474885	10.474885	

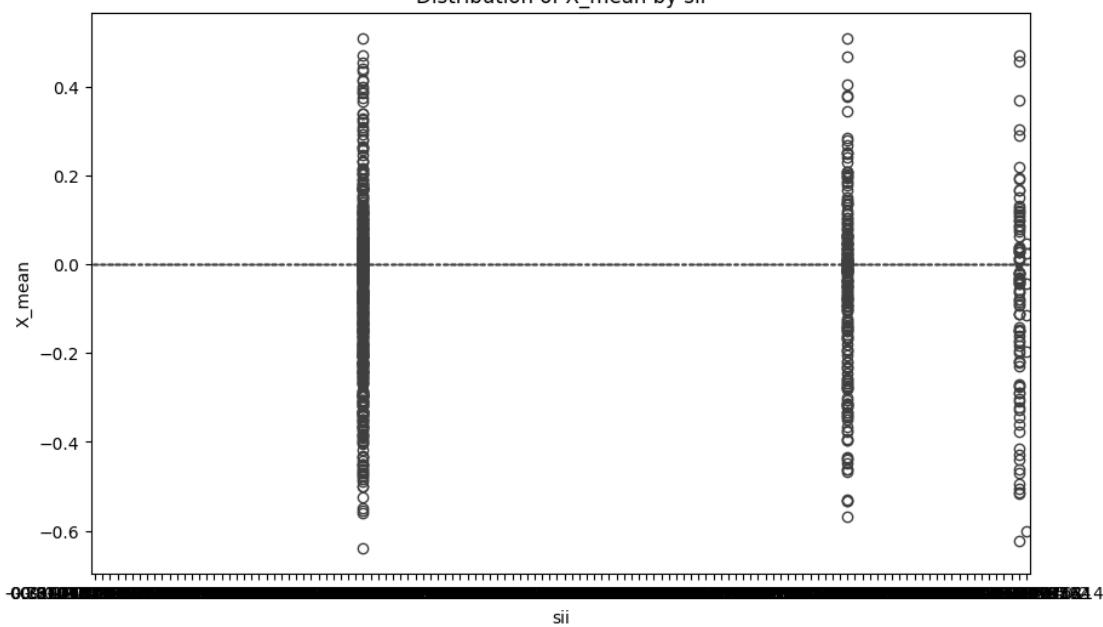
PCIAT-PCIAT_Total						SDS-Season	\
	mean	std	min	max	mean	std	min
sii							
-0.760696	8.770492	NaN	8.770492	8.770492	0.467407	NaN	0.467407
-0.314713	8.770492	NaN	8.770492	8.770492	0.467407	NaN	0.467407
-0.312714	8.770492	NaN	8.770492	8.770492	0.512539	NaN	0.512539
-0.231091	8.770492	NaN	8.770492	8.770492	0.467407	NaN	0.467407
-0.144216	8.770492	NaN	8.770492	8.770492	0.467407	NaN	0.467407

SDS-SDS_Total_Raw							\	
	max	mean	std	min	max			
sii								
-0.760696	0.467407	41.230775	NaN	41.230775	41.230775			
-0.314713	0.467407	39.890807	NaN	39.890807	39.890807			
-0.312714	0.512539	35.000000	NaN	35.000000	35.000000			
-0.231091	0.467407	41.250020	NaN	41.250020	41.250020			
-0.144216	0.467407	40.134626	NaN	40.134626	40.134626			
SDS-SDS_Total_T							\	
	mean	std	min	max		mean	std	
sii								
-0.760696	57.417806	NaN	57.417806	57.417806		0.602178	NaN	
-0.314713	56.442597	NaN	56.442597	56.442597		0.486120	NaN	
-0.312714	50.000000	NaN	50.000000	50.000000		0.457262	NaN	
-0.231091	57.776421	NaN	57.776421	57.776421		0.602178	NaN	
-0.144216	56.311069	NaN	56.311069	56.311069		0.486120	NaN	
PreInt_EduHx-Season							\	
	min	max				mean	std	
sii								
-0.760696	0.602178	0.602178				3.000000	NaN	
-0.314713	0.486120	0.486120				3.000000	NaN	
-0.312714	0.457262	0.457262				2.814750	NaN	
-0.231091	0.602178	0.602178				1.475126	NaN	
-0.144216	0.486120	0.486120				1.318443	NaN	
PreInt_EduHx-computerinternet_hoursday							\	
	min	max				mean	std	
sii								
-0.760696	0.602178	0.602178				3.000000	NaN	
-0.314713	0.486120	0.486120				3.000000	NaN	
-0.312714	0.457262	0.457262				2.814750	NaN	
-0.231091	0.602178	0.602178				1.475126	NaN	
-0.144216	0.486120	0.486120				1.318443	NaN	
sii							\	
	min	max	mean	std	min	max	mean	
sii								
-0.760696	3.000000	3.000000	-0.760696	NaN	-0.760696	-0.760696	0.973770	NaN
-0.314713	3.000000	3.000000	-0.314713	NaN	-0.314713	-0.314713	0.499136	NaN
-0.312714	2.814750	2.814750	-0.312714	NaN	-0.312714	-0.312714	0.973770	NaN
-0.231091	1.475126	1.475126	-0.231091	NaN	-0.231091	-0.231091	0.855589	NaN
-0.144216	1.318443	1.318443	-0.144216	NaN	-0.144216	-0.144216	0.855589	NaN
PCIAT_Cluster							\	
	min	max	mean	std	min	max		
sii								
-0.760696	0.973770	0.973770	0.0	NaN	0.0	0.0		
-0.314713	0.499136	0.499136	0.0	NaN	0.0	0.0		
-0.312714	0.973770	0.973770	0.0	NaN	0.0	0.0		
-0.231091	0.855589	0.855589	0.0	NaN	0.0	0.0		
-0.144216	0.855589	0.855589	0.0	NaN	0.0	0.0		
CGAS-CGAS_Score_x_SDS-SDS_Total_Raw							\	
	mean	std	min	max				
sii								

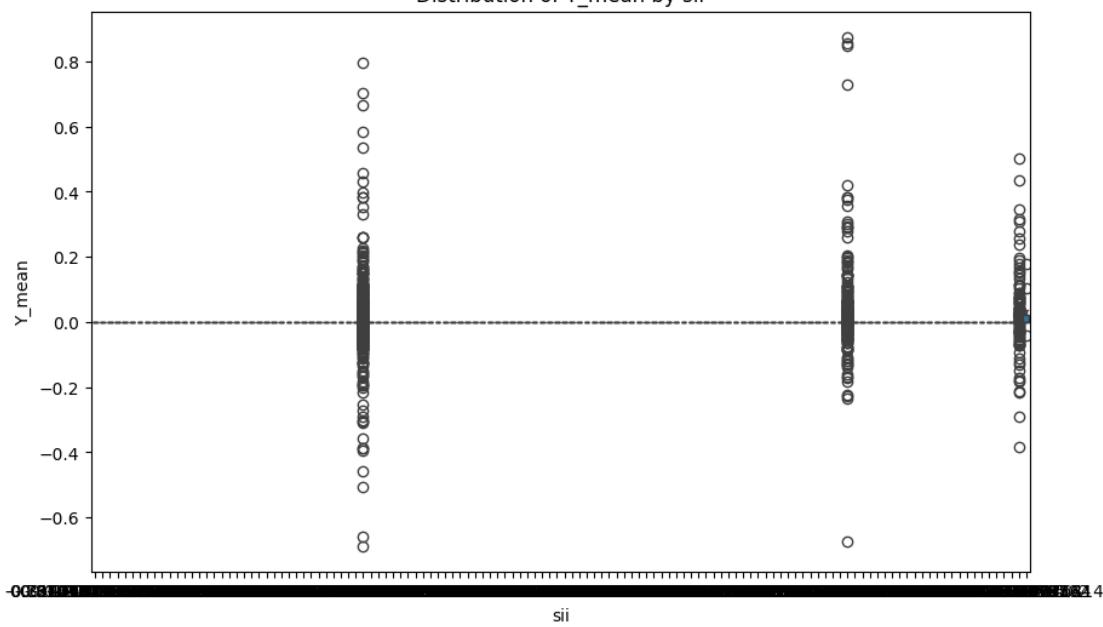
-0.760696		2363.884081	NaN	2363.884081	2363.884081									
-0.314713		3018.565478	NaN	3018.565478	3018.565478									
-0.312714		2660.000000	NaN	2660.000000	2660.000000									
-0.231091		2447.538500	NaN	2447.538500	2447.538500									
-0.144216		2864.127094	NaN	2864.127094	2864.127094									
CGAS-CGAS_Score_x_Physical-BMI														
		mean	std	min	max	X_mean	\							
sii						mean								
-0.760696		1382.729398	NaN	1382.729398	1382.729398	0.0								
-0.314713		1954.256805	NaN	1954.256805	1954.256805	0.0								
-0.312714		2263.981151	NaN	2263.981151	2263.981151	0.0								
-0.231091		1011.853132	NaN	1011.853132	1011.853132	0.0								
-0.144216		1256.767284	NaN	1256.767284	1256.767284	0.0								
X_std														
	std	min	max	mean	std	min	max	X_min	X_max	\				
sii								mean	std					
-0.760696	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	0.0	NaN				
-0.314713	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	0.0	NaN				
-0.312714	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	0.0	NaN				
-0.231091	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	0.0	NaN				
-0.144216	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	0.0	NaN				
Y_mean														
	min	max	mean	std	min	max	mean	std	min	max	Y_min	\		
sii								mean	std	min				
-0.760696	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN		
-0.314713	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN		
-0.312714	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN		
-0.231091	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN		
-0.144216	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN		
Y_max														
	max	mean	std	min	max	mean	std	min	max	mean	std	Z_std	\	
sii														
-0.760696	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.314713	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.312714	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.231091	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.144216	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
Z_min														
	mean	std	min	max	mean	std	min	max	enmo_mean	mean	std	min	max	\
sii														
-0.760696	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	
-0.314713	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	
-0.312714	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	0.0	

	relative_date_PCIAT_mean				fourier_X_real				\
	mean	std	min	max	mean	std	min	max	
sii									
-0.760696	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.314713	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.312714	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.231091	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.144216	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
	fourier_X_imag				fourier_Y_real				\
	mean	std	min	max	mean	std	min	max	
sii									
-0.760696	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.314713	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.312714	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.231091	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.144216	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
	fourier_Y_imag				fourier_Z_real				\
	mean	std	min	max	mean	std	min	max	
sii									
-0.760696	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.314713	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.312714	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.231091	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.144216	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
	fourier_Z_imag				activity_during_day				\
	mean	std	min	max	mean	std	min	max	
sii									
-0.760696	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.314713	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.312714	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.231091	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.144216	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
	activity_during_night				activity_ratio_day_night				\
	mean	std	min	max	mean	std	min	max	
sii									
-0.760696	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.314713	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.312714	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.231091	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
-0.144216	0.0	NaN	0.0	0.0	0.0	NaN	0.0	0.0	
	non_wear_proportion				sedentary_proportion				\
	min	max	mean	std	min	max	mean	std	
sii									

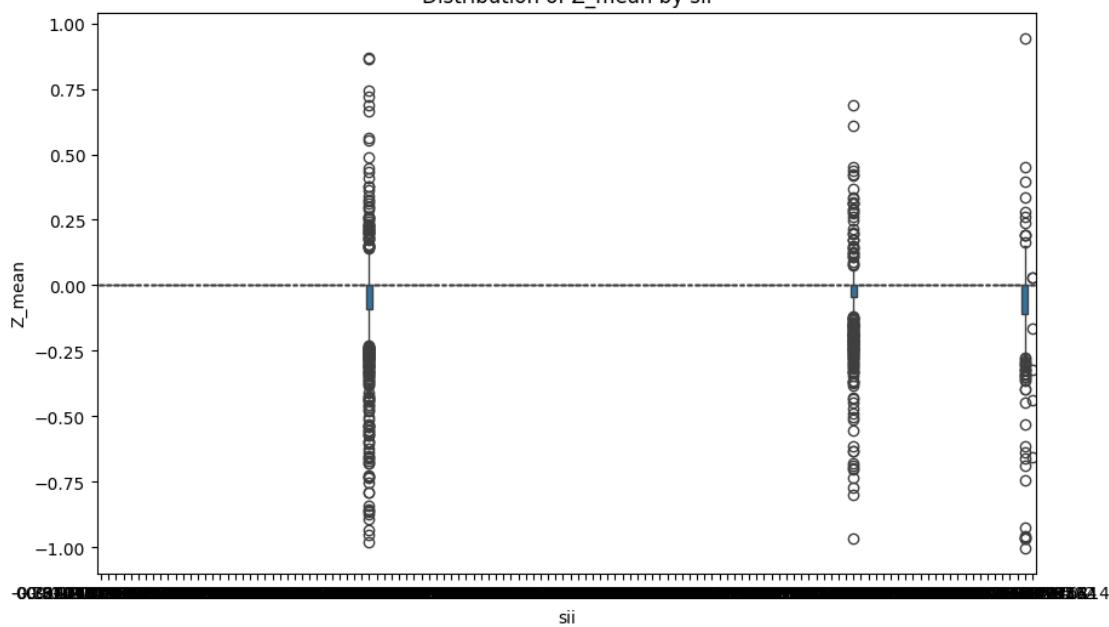
Distribution of X_mean by sii



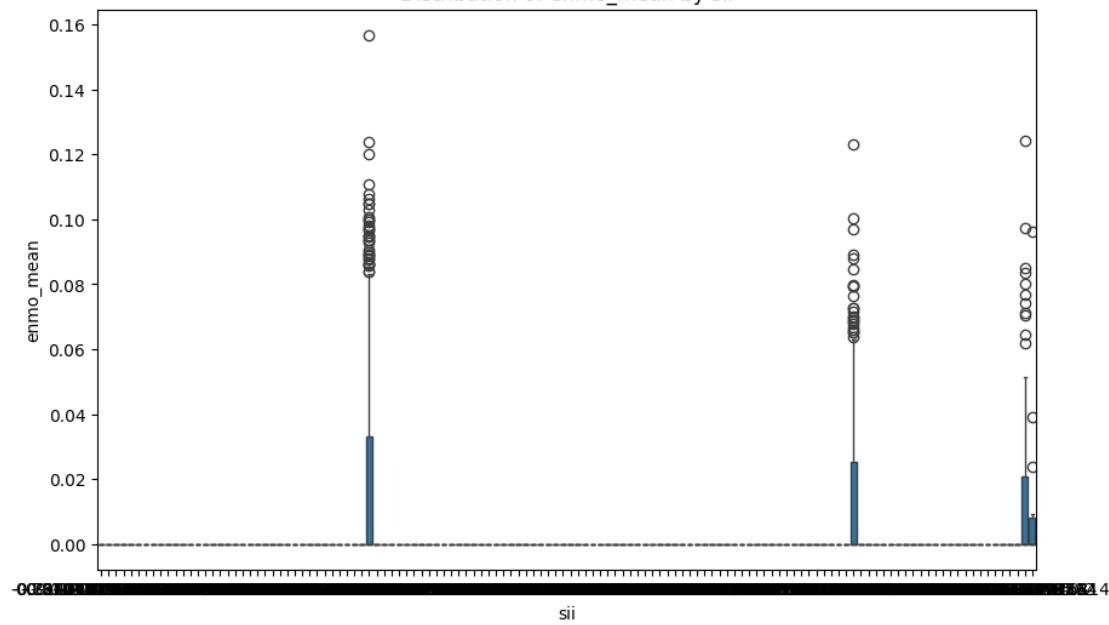
Distribution of Y_mean by sii



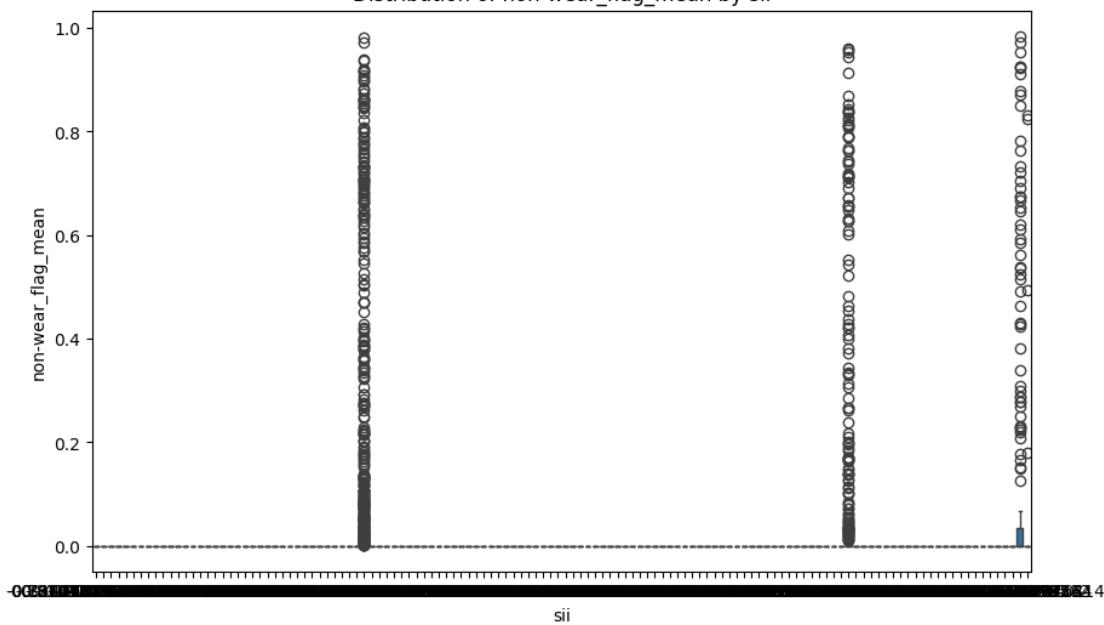
Distribution of Z_mean by sii



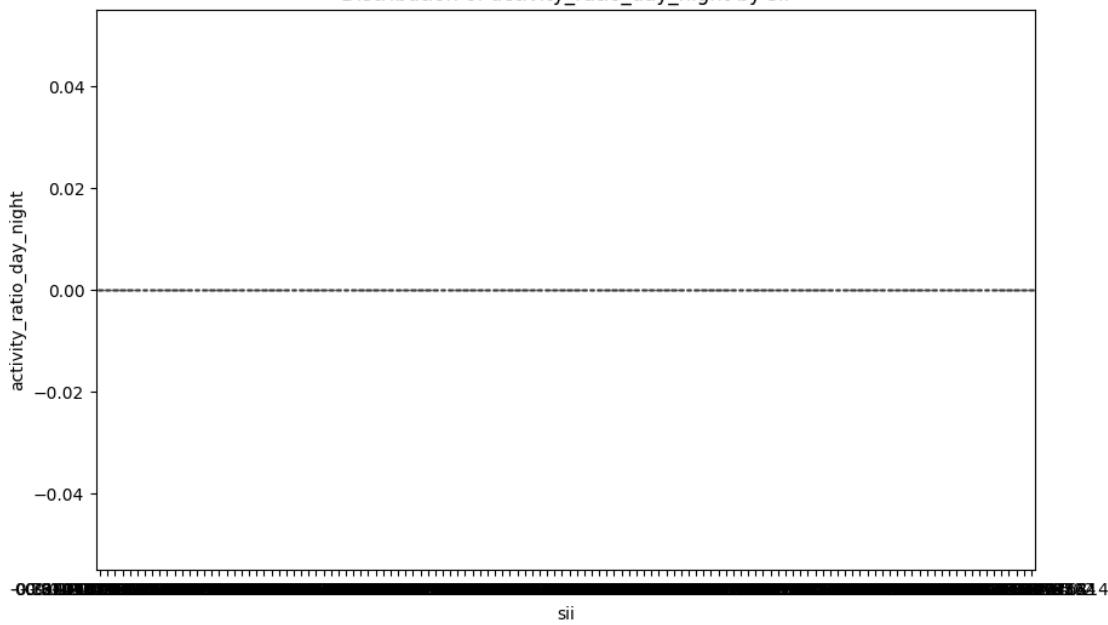
Distribution of enmo_mean by sii

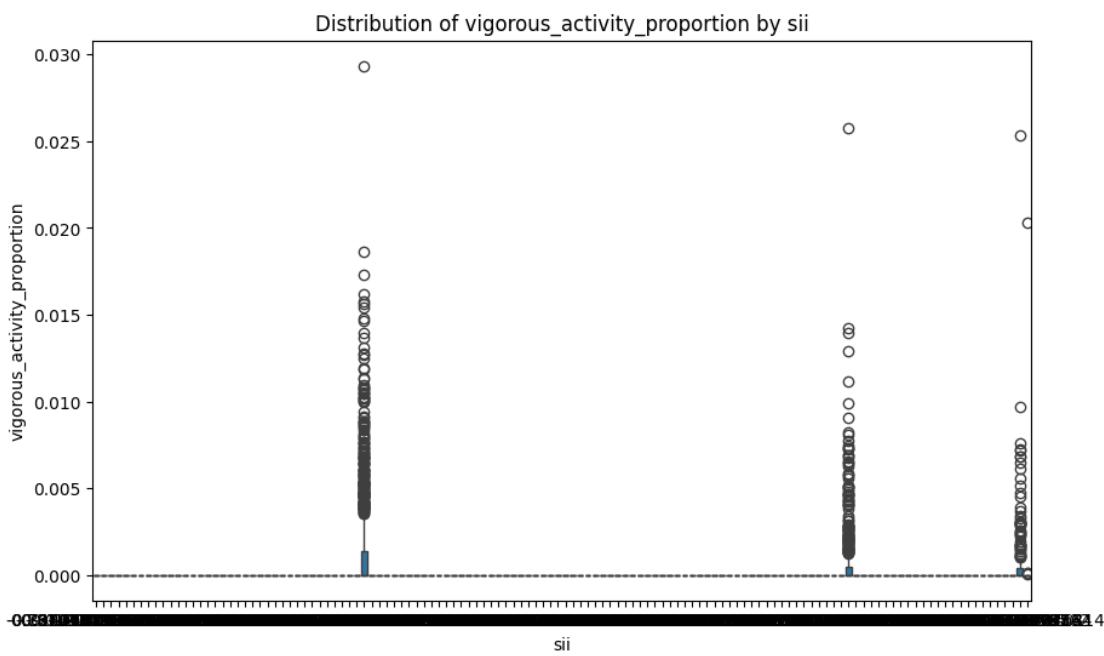
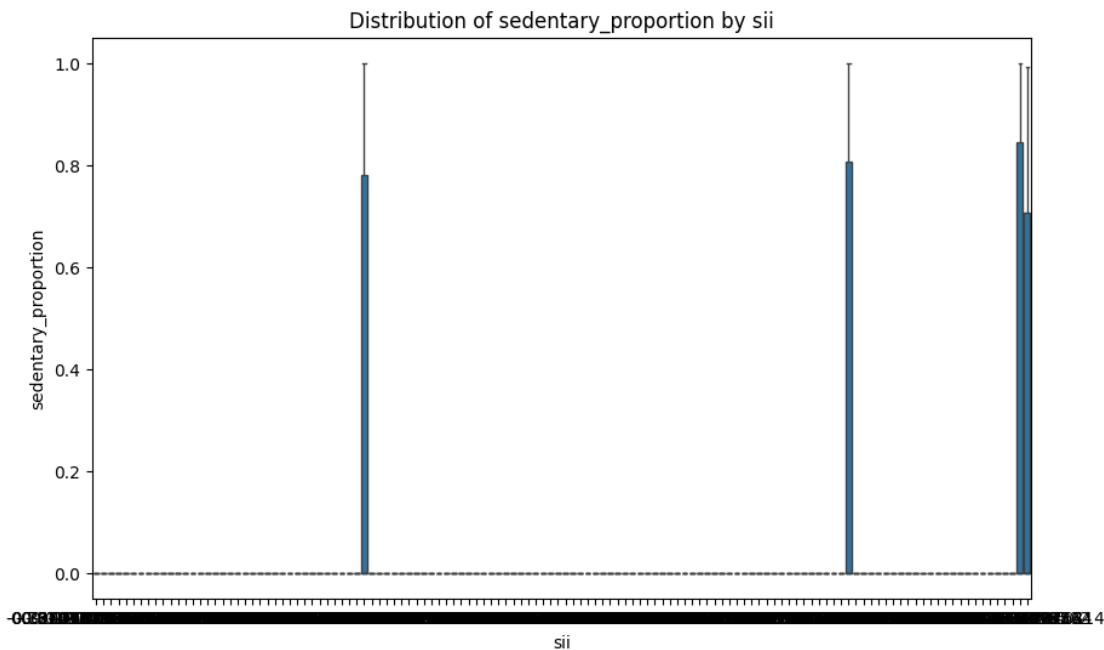


Distribution of non-wear_flag_mean by sii



Distribution of activity_ratio_day_night by sii





```
[46]: merged_train_df.shape
```

```
[46]: (3045, 105)
```

```
[47]: from imblearn.over_sampling import SMOTE
# Convert the 'sii' column to integer type to ensure it is treated as categorical
merged_train_df['sii'] = merged_train_df['sii'].astype(int)

merged_train_df['id_numeric'] = pd.factorize(merged_train_df['id'])[0]
id_mapping = dict(zip(merged_train_df['id_numeric'], merged_train_df['id']))

# Extract the features and target variable 'sii' from the merged dataframe
features = merged_train_df.drop(columns=['sii', 'id']) # Exclude 'sii' and 'id' columns
target = merged_train_df['sii']

# Apply SMOTE to balance the 'sii' classes
smote = SMOTE(random_state=42)
features_resampled, target_resampled = smote.fit_resample(features, target)

# Create a new DataFrame for the oversampled dataset
oversampled_df = pd.DataFrame(features_resampled, columns=features.columns)
oversampled_df['sii'] = target_resampled

# Display the class distribution after SMOTE
print("Class distribution after SMOTE oversampling:")
print(oversampled_df['sii'].value_counts())
```

Class distribution after SMOTE oversampling:

```
sii
2    2053
0    2053
1    2053
3    2053
Name: count, dtype: int64
```

```
/var/tmp/ipykernel_7796/2866646705.py:18: PerformanceWarning: DataFrame is
highly fragmented. This is usually the result of calling `frame.insert` many
times, which has poor performance. Consider joining all columns at once using
pd.concat(axis=1) instead. To get a de-fragmented frame, use `newframe =
frame.copy()`
oversampled_df['sii'] = target_resampled
```

```
[48]: oversampled_df['id'] = oversampled_df['id_numeric'].map(id_mapping)
oversampled_df = oversampled_df.drop(columns = ['id_numeric'])
```

```
/var/tmp/ipykernel_7796/3770237215.py:1: PerformanceWarning: DataFrame is highly
fragmented. This is usually the result of calling `frame.insert` many times,
which has poor performance. Consider joining all columns at once using
pd.concat(axis=1) instead. To get a de-fragmented frame, use `newframe =
```

```
frame.copy()
oversampled_df['id'] = oversampled_df['id_numeric'].map(id_mapping)
```

```
[49]: oversampled_df.head()
```

```
[49]:    Basic_Demos-Enroll_Season  Basic_Demos-Age  Basic_Demos-Sex  CGAS-Season \
0                  0.559547          5.0            0.0      0.527092
1                  0.543858         10.0            1.0      0.538294
2                  0.598983          9.0            0.0      0.538294
3                  0.475815         13.0            1.0      0.527092
4                  0.559547         11.0            0.0      0.515994

   CGAS-CGAS_Score  Physical-Season  Physical-BMI  Physical-Height \
0              51.0        0.526350    16.877316     46.000000
1              71.0        0.526350    16.648696     56.500000
2              71.0        0.516702    18.292347     56.000000
3              50.0        0.516702    22.279952     59.500000
4              66.0        0.471466    18.269958     55.568097

  Physical-Weight  Physical-Waist_Circumference  Physical-Diastolic_BP \
0      50.800000                  23.154724           69.273255
1      75.600000                  25.755813           65.000000
2      81.600000                  30.237799           60.000000
3     112.200000                  33.812417           60.000000
4      83.565122                  26.013867           69.317251

  Physical-HeartRate  Physical-Systolic_BP  Fitness_Endurance-Season \
0       86.942701          111.584992           0.562024
1      94.000000          117.000000           0.416561
2      97.000000          117.000000           0.419733
3      73.000000          102.000000           0.562024
4      84.110761          116.626216           0.562024

Fitness_Endurance-Max_Stage  Fitness_Endurance-Time_Mins \
0                  4.661823           5.902407
1                  5.000000           7.000000
2                  6.000000           9.000000
3                  3.781508           6.496836
4                  4.861046           8.019364

Fitness_Endurance-Time_Sec  FGC-Season  FGC-FGC CU  FGC-FGC CU_Zone \
0          30.190591      0.539792    0.000000     0.000000
1          33.000000      0.539792   20.000000    1.000000
2          37.000000      0.531007   18.000000    1.000000
3          24.040340      0.531007   12.000000    0.000000
4          28.006224      0.552717   10.701686    0.455832
```

	FGC-FGC_GSND	FGC-FGC_GSND_Zone	FGC-FGC_GSD	FGC-FGC_GSD_Zone	FGC-FGC_PU	\
0	12.457159	1.861092	7.105427	2.104217	0.000000	
1	10.200000	1.000000	14.700000	2.000000	7.000000	
2	15.489000	1.797822	17.595300	2.176744	5.000000	
3	16.500000	2.000000	17.900000	2.000000	6.000000	
4	19.270922	1.683190	19.325191	1.630797	5.096538	
	FGC-FGC_PU_Zone	FGC-FGC_SRL	FGC-FGC_SRL_Zone	FGC-FGC_SRR	FGC-FGC_SRR_Zone	\
0	0.000000	7.000000	0.000000	6.000000	0.000000	
1	1.000000	10.000000	1.000000	10.000000	1.000000	
2	0.000000	7.000000	0.000000	7.000000	0.000000	
3	0.000000	10.000000	1.000000	11.000000	1.000000	
4	0.302039	8.751021	0.68659	8.92129	0.68659	
	FGC-FGC_SRR_Zone	FGC-FGC_TL	FGC-FGC_TL_Zone	BIA-Season	BIA-BIA_Activity_Level_num	\
0	0.000000	6.000000	1.000000	0.534475	2.000000	
1	1.000000	5.000000	0.000000	0.490251	2.658187	
2	0.000000	7.000000	1.000000	0.566098	3.000000	
3	1.000000	8.000000	0.000000	0.566098	2.000000	
4	0.690292	9.021283	0.723361	0.490251	2.517398	
	BIA-BIA_Activity_Level_num	BIA-BIA_BMC	BIA-BIA_BMI	BIA-BIA_BMR	BIA-BIA_DEE	\
0	2.000000	2.668550	16.879200	932.498000	1492.000000	
1	2.658187	7.660622	18.540298	1229.028902	2004.524112	
2	3.000000	3.841910	18.294300	1131.430000	1923.440000	
3	2.000000	4.330360	30.186500	1330.970000	1996.450000	
4	2.517398	7.660620	18.540307	1229.029934	2020.016337	
	BIA-BIA_DEE	BIA-BIA_ECW	BIA-BIA_FFM	BIA-BIA_FFFI	BIA-BIA_FMI	\
0	1492.000000	8.255980	41.586200	13.817700	3.061430	
1	2004.524112	20.415826	73.170824	14.810861	3.729442	
2	1923.440000	15.592500	62.775700	14.074000	4.220330	
3	1996.450000	30.212400	84.028500	16.687700	13.498800	
4	2020.016337	20.415797	73.170847	14.810861	3.729442	
	BIA-BIA_Fat	BIA-BIA_Frame_num	BIA-BIA_ICW	BIA-BIA_LDM	BIA-BIA_LST	\
0	9.213770	1.000000	24.434900	8.895360	38.917700	
1	5.294715	1.531391	32.829003	19.926022	65.510201	
2	18.824300	2.000000	30.404100	16.779000	58.933800	
3	67.971500	2.000000	32.914100	20.902000	79.698200	
4	10.512782	1.644971	32.829002	19.926031	65.510206	
	BIA-BIA_SMM	BIA-BIA_TBW	PAQ_A-Season	PAQ_A-PAQ_A_Total	PAQ_C-Season	\
0	19.541300	32.690900	0.480263	1.773888	0.460443	
1	42.760486	53.244807	0.480263	1.991617	0.544231	
2	26.479800	45.996600	0.480263	1.978289	0.716160	
3	35.380400	63.126500	0.480263	1.968692	0.579612	

4	29.831805	53.244809	0.480263	2.110197	0.716160			
0	PAQ_C-PAQ_C_Total	PCIAT-PCIAT_Total	SDS-Season	SDS-SDS_Total_Raw	\	2.68491		
1			55.0	0.467407		2.17000		
2			28.0	0.515460		2.45100		
3			44.0	0.512539		4.11000		
4			34.0	0.512539		1.10000		
			10.0	0.611293				
0	SDS-SDS_Total_T	PreInt_EduHx-Season	\			59.348885		
1			0.564223			54.000000		
2			0.534033			45.000000		
3			0.602178			56.000000		
4			0.486120			59.000000		
			0.564223					
0	PreInt_EduHx-computerinternet_hoursday	Age_Group	PCIAT_Cluster	\				
1		3.0	0.443345			5.0		
2		2.0	0.362030			7.0		
3		0.0	0.362030			4.0		
4		0.0	0.855589			3.0		
		0.0	0.855589			3.0		
0	CGAS-CGAS_Score_x_SDSDS_Total_Raw	CGAS-CGAS_Score_x_Physical-BMI	\			2156.462944		
1				860.743100		2698.000000		
2				1182.057420		2201.000000		
3				1298.756633		2000.000000		
4				1113.997599		2772.000000		
				1206.032260				
0	X_mean	X_std	X_min	X_max	Y_mean	Y_std	Y_min	\
1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
3	-0.316384	0.453665	-1.746094	1.507865	0.016009	0.502702	-2.905339	
4	-0.004272	0.351545	-1.038711	1.034351	0.016859	0.303812	-1.522690	
	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
0	Y_max	Z_mean	Z_std	Z_min	Z_max	enmo_mean	enmo_std	\
1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
3	1.666354	-0.167890	0.585710	-1.048372	1.546979	0.047388	0.106351	
4	1.946303	-0.631731	0.623476	-1.018787	1.146284	0.011926	0.024331	
	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
0	anglez_mean	anglez_std	non-wear_flag_mean	light_mean	light_std	\		
1	0.000000	0.000000		0.000000	0.000000			
	0.000000	0.000000		0.000000	0.000000			

2	-10.580416	42.947170	0.000000	42.29631	208.168976
3	-55.630768	50.303635	0.655708	16.77198	95.327438
4	0.000000	0.000000	0.000000	0.000000	0.000000
	battery_voltage_mean	battery_voltage_std	time_of_day_mean	weekday_mean	\
0	0.000000	0.000000	0.000000e+00	0.000000	
1	0.000000	0.000000	0.000000e+00	0.000000	
2	4053.578857	112.404037	5.046215e+13	4.470182	
3	3838.189453	155.573868	4.321212e+13	3.909848	
4	0.000000	0.000000	0.000000e+00	0.000000	
	quarter_mean	relative_date_PCIAT_mean	fourier_X_real	fourier_X_imag	\
0	0.0	0.000000	0.000000	0.000000e+00	
1	0.0	0.000000	0.000000	0.000000e+00	
2	3.0	53.201683	-2653.531675	-1.083578e-14	
3	3.0	79.435593	4103.865122	-1.680035e+03	
4	0.0	0.000000	0.000000	0.000000e+00	
	fourier_Y_real	fourier_Y_imag	fourier_Z_real	fourier_Z_imag	\
0	0.000000	0.000000	0.000000	0.000000e+00	
1	0.000000	0.000000	0.000000	0.000000e+00	
2	705.803060	-207.446683	1995.401835	-5.684342e-15	
3	14385.071425	3120.930726	-26765.674436	-8.731149e-12	
4	0.000000	0.000000	0.000000	0.000000e+00	
	activity_during_day	activity_during_night	activity_ratio_day_night		\
0	0.0	0.000000	0.0		
1	0.0	0.000000	0.0		
2	0.0	2053.305176	0.0		
3	0.0	4727.518555	0.0		
4	0.0	0.000000	0.0		
	non_wear_proportion	sedentary_proportion	light_activity_proportion		\
0	0.000000	0.000000	0.000000		
1	0.000000	0.000000	0.000000		
2	0.000000	0.792453	0.198131		
3	0.655708	0.978501	0.021171		
4	0.000000	0.000000	0.000000		
	moderate_activity_proportion	vigorous_activity_proportion			\
0	0.000000	0.000000			
1	0.000000	0.000000			
2	0.007870	0.001546			
3	0.000288	0.000040			
4	0.000000	0.000000			
	actigraphy_present	sii	id		

```
0          0    2  00008ff9
1          0    0  00105258
2          1    1  00115b9f
3          1    1  001f3379
4          0    0  00abe655
```

```
[50]: list(oversampled_df.columns)
```

```
[50]: ['Basic_Demos-Enroll_Season',
       'Basic_Demos-Age',
       'Basic_Demos-Sex',
       'CGAS-Season',
       'CGAS-CGAS_Score',
       'Physical-Season',
       'Physical-BMI',
       'Physical-Height',
       'Physical-Weight',
       'Physical-Waist_Circumference',
       'Physical-Diastolic_BP',
       'Physical-HeartRate',
       'Physical-Systolic_BP',
       'Fitness_Endurance-Season',
       'Fitness_Endurance-Max_Stage',
       'Fitness_Endurance-Time_Mins',
       'Fitness_Endurance-Time_Sec',
       'FGC-Season',
       'FGC-FGC CU',
       'FGC-FGC CU_Zone',
       'FGC-FGC GSND',
       'FGC-FGC GSND_Zone',
       'FGC-FGC GSD',
       'FGC-FGC GSD_Zone',
       'FGC-FGC PU',
       'FGC-FGC PU_Zone',
       'FGC-FGC SRL',
       'FGC-FGC SRL_Zone',
       'FGC-FGC SRR',
       'FGC-FGC SRR_Zone',
       'FGC-FGC TL',
       'FGC-FGC TL_Zone',
       'BIA-Season',
       'BIA-BIA_Activity_Level_num',
       'BIA-BIA_BMC',
       'BIA-BIA_BMI',
       'BIA-BIA_BMR',
       'BIA-BIA_DEE',
       'BIA-BIA_ECW',
```

```
'BIA-BIA_FFM',
'BIA-BIA_FFFI',
'BIA-BIA_FMI',
'BIA-BIA_Fat',
'BIA-BIA_Frame_num',
'BIA-BIA_ICW',
'BIA-BIA_LDM',
'BIA-BIA_LST',
'BIA-BIA_SMM',
'BIA-BIA_TBW',
'PAQ_A-Season',
'PAQ_A-PAQ_A_Total',
'PAQ_C-Season',
'PAQ_C-PAQ_C_Total',
'PCIAT-PCIAT_Total',
'SDS-Season',
'SDS-SDS_Total_Raw',
'SDS-SDS_Total_T',
'PreInt_EduHx-Season',
'PreInt_EduHx-computerinternet_hoursday',
'Age_Group',
'PCIAT_Cluster',
'CGAS-CGAS_Score_x_SDS-SDS_Total_Raw',
'CGAS-CGAS_Score_x_Physical-BMI',
'X_mean',
'X_std',
'X_min',
'X_max',
'Y_mean',
'Y_std',
'Y_min',
'Y_max',
'Z_mean',
'Z_std',
'Z_min',
'Z_max',
'enmo_mean',
'enmo_std',
'anglez_mean',
'anglez_std',
'non-wear_flag_mean',
'light_mean',
'light_std',
'battery_voltage_mean',
'battery_voltage_std',
'time_of_day_mean',
'weekday_mean',
```

```
'quarter_mean',
'relative_date_PCIAT_mean',
'fourier_X_real',
'fourier_X_imag',
'fourier_Y_real',
'fourier_Y_imag',
'fourier_Z_real',
'fourier_Z_imag',
'activity_during_day',
'activity_during_night',
'activity_ratio_day_night',
'non_wear_proportion',
'sedentary_proportion',
'light_activity_proportion',
'moderate_activity_proportion',
'vegrous_activity_proportion',
'actigraphy_present',
'sii',
'id']
```

```
[51]: oversampled_df.shape
```

```
[51]: (8212, 105)
```

```
[52]: !pip install tensorflow
```

```
Requirement already satisfied: tensorflow in /opt/conda/lib/python3.10/site-packages (2.17.0)
Requirement already satisfied: absl-py>=1.0.0 in /opt/conda/lib/python3.10/site-packages (from tensorflow) (2.1.0)
Requirement already satisfied: astunparse>=1.6.0 in /opt/conda/lib/python3.10/site-packages (from tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=24.3.25 in /opt/conda/lib/python3.10/site-packages (from tensorflow) (24.3.25)
Requirement already satisfied: gast!=0.5.0,!0.5.1,!0.5.2,>=0.2.1 in /opt/conda/lib/python3.10/site-packages (from tensorflow) (0.6.0)
Requirement already satisfied: google-pasta>=0.1.1 in /opt/conda/lib/python3.10/site-packages (from tensorflow) (0.2.0)
Requirement already satisfied: h5py>=3.10.0 in /opt/conda/lib/python3.10/site-packages (from tensorflow) (3.12.1)
Requirement already satisfied: libclang>=13.0.0 in /opt/conda/lib/python3.10/site-packages (from tensorflow) (18.1.1)
Requirement already satisfied: ml-dtypes<0.5.0,>=0.3.1 in /opt/conda/lib/python3.10/site-packages (from tensorflow) (0.4.1)
Requirement already satisfied: opt-einsum>=2.3.2 in /opt/conda/lib/python3.10/site-packages (from tensorflow) (3.4.0)
Requirement already satisfied: packaging in /opt/conda/lib/python3.10/site-packages (from tensorflow) (24.1)
```

```
Requirement already satisfied:  
protobuf!=4.21.0,!>=4.21.1,!>=4.21.2,!>=4.21.3,!>=4.21.4,!>=4.21.5,<5.0.0dev,>=3.20.3  
in /opt/conda/lib/python3.10/site-packages (from tensorflow) (3.20.3)  
Requirement already satisfied: requests<3,>=2.21.0 in  
/opt/conda/lib/python3.10/site-packages (from tensorflow) (2.32.3)  
Requirement already satisfied: setuptools in /opt/conda/lib/python3.10/site-  
packages (from tensorflow) (73.0.1)  
Requirement already satisfied: six>=1.12.0 in /opt/conda/lib/python3.10/site-  
packages (from tensorflow) (1.16.0)  
Requirement already satisfied: termcolor>=1.1.0 in  
/opt/conda/lib/python3.10/site-packages (from tensorflow) (2.4.0)  
Requirement already satisfied: typing-extensions>=3.6.6 in  
/opt/conda/lib/python3.10/site-packages (from tensorflow) (4.12.2)  
Requirement already satisfied: wrapt>=1.11.0 in /opt/conda/lib/python3.10/site-  
packages (from tensorflow) (1.16.0)  
Requirement already satisfied: grpcio<2.0,>=1.24.3 in  
/opt/conda/lib/python3.10/site-packages (from tensorflow) (1.66.1)  
Requirement already satisfied: tensorboard<2.18,>=2.17 in  
/opt/conda/lib/python3.10/site-packages (from tensorflow) (2.17.1)  
Requirement already satisfied: keras>=3.2.0 in /opt/conda/lib/python3.10/site-  
packages (from tensorflow) (3.6.0)  
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in  
/opt/conda/lib/python3.10/site-packages (from tensorflow) (0.37.1)  
Requirement already satisfied: numpy<2.0.0,>=1.23.5 in  
/opt/conda/lib/python3.10/site-packages (from tensorflow) (1.26.4)  
Requirement already satisfied: wheel<1.0,>=0.23.0 in  
/opt/conda/lib/python3.10/site-packages (from astunparse>=1.6.0->tensorflow)  
(0.44.0)  
Requirement already satisfied: rich in /opt/conda/lib/python3.10/site-packages  
(from keras>=3.2.0->tensorflow) (13.8.1)  
Requirement already satisfied: namex in /opt/conda/lib/python3.10/site-packages  
(from keras>=3.2.0->tensorflow) (0.0.8)  
Requirement already satisfied: optree in /opt/conda/lib/python3.10/site-packages  
(from keras>=3.2.0->tensorflow) (0.13.0)  
Requirement already satisfied: charset-normalizer<4,>=2 in  
/opt/conda/lib/python3.10/site-packages (from requests<3,>=2.21.0->tensorflow)  
(3.3.2)  
Requirement already satisfied: idna<4,>=2.5 in /opt/conda/lib/python3.10/site-  
packages (from requests<3,>=2.21.0->tensorflow) (3.8)  
Requirement already satisfied: urllib3<3,>=1.21.1 in  
/opt/conda/lib/python3.10/site-packages (from requests<3,>=2.21.0->tensorflow)  
(1.26.20)  
Requirement already satisfied: certifi>=2017.4.17 in  
/opt/conda/lib/python3.10/site-packages (from requests<3,>=2.21.0->tensorflow)  
(2024.8.30)  
Requirement already satisfied: markdown>=2.6.8 in  
/opt/conda/lib/python3.10/site-packages (from  
tensorboard<2.18,>=2.17->tensorflow) (3.7)
```

```

Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in
/opt/conda/lib/python3.10/site-packages (from
tensorboard<2.18,>=2.17->tensorflow) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in
/opt/conda/lib/python3.10/site-packages (from
tensorboard<2.18,>=2.17->tensorflow) (3.0.4)
Requirement already satisfied: MarkupSafe>=2.1.1 in
/opt/conda/lib/python3.10/site-packages (from
werkzeug>=1.0.1->tensorboard<2.18,>=2.17->tensorflow) (2.1.5)
Requirement already satisfied: markdown-it-py>=2.2.0 in
/opt/conda/lib/python3.10/site-packages (from rich->keras>=3.2.0->tensorflow)
(3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in
/opt/conda/lib/python3.10/site-packages (from rich->keras>=3.2.0->tensorflow)
(2.18.0)
Requirement already satisfied: mdurl~=0.1 in /opt/conda/lib/python3.10/site-
packages (from markdown-it-py>=2.2.0->rich->keras>=3.2.0->tensorflow) (0.1.2)

```

```

[53]: import tensorflow as tf

def focal_loss(gamma=2.0, alpha=0.25):
    """
    Focal loss implementation as described in the paper: https://arxiv.org/abs/1708.02002

    Args:
        gamma: Focusing parameter. Default is 2.0.
        alpha: Balance parameter for class imbalance. Default is 0.25.

    Returns:
        loss function to be used in model.compile()
    """
    def focal_loss_fixed(y_true, y_pred):
        # Clip the predictions to avoid log(0) errors
        y_pred = tf.clip_by_value(y_pred, 1e-7, 1.0 - 1e-7)

        # Calculate cross entropy
        cross_entropy = -y_true * tf.math.log(y_pred)

        # Calculate focal loss
        loss = alpha * tf.pow(1 - y_pred, gamma) * cross_entropy
        return tf.reduce_mean(tf.reduce_sum(loss, axis=-1))

    return focal_loss_fixed

```

2024-10-10 07:35:38.725310: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them

off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.

2024-10-10 07:35:38.767850: I external/local_xla/xla/tsl/cuda/cudart_stub.cc:32] Could not find cuda drivers on your machine, GPU will not be used.

2024-10-10 07:35:40.214014: I external/local_xla/xla/tsl/cuda/cudart_stub.cc:32] Could not find cuda drivers on your machine, GPU will not be used.

2024-10-10 07:35:40.520301: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:485] Unable to register cuFFT factory: Attempting to register factory for plugin cuFFT when one has already been registered

2024-10-10 07:35:40.899942: E external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:8454] Unable to register cuDNN factory: Attempting to register factory for plugin cuDNN when one has already been registered

2024-10-10 07:35:40.973865: E external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1452] Unable to register cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has already been registered

2024-10-10 07:35:41.925048: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.

To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.

```
[54]: import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, Dropout, Input, BatchNormalization,
    ↪LeakyReLU, LSTM, Conv1D, GlobalAveragePooling1D, MultiHeadAttention, Reshape
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score, f1_score
from tensorflow.keras.regularizers import l2, l1_l2
from tensorflow.keras.losses import CategoricalCrossentropy
#from tensorflow_addons.losses import SigmoidFocalCrossEntropy

# Separate features and target from the merged dataset
teacher_features = oversampled_df.drop(columns=['sii', 'id',
    ↪'actigraphy_present']) # All columns except 'sii' and 'id'
teacher_target = oversampled_df['sii'] # Target variable

# Split the oversampled dataset into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(
    oversampled_df.drop(columns=['sii', 'id']), oversampled_df['sii'],
    ↪test_size=0.2, random_state=42
)

def create_teacher_model(architecture='A', input_shape=None):
```

```

model = Sequential()

# Dynamically set input shape if not provided
if input_shape is None:
    raise ValueError("Input shape must be specified for model creation.")

# Add the input layer
model.add(Input(shape=(input_shape,)))

# Choose architecture A or B
if architecture == 'A':
    # OLD Model A - Previous architectures and classification reports
    # TEST #1 ~ 62% accuracy
    # Teacher Model Performance on Validation Set: (model A)
    # Accuracy: 0.6207
    # F1-Score: 0.6437
    # Classification Report:
    #
    # precision recall f1-score support
    # 0 0.86 0.70 0.77 401
    # 1 0.36 0.51 0.42 154
    # 2 0.31 0.40 0.35 50
    # 3 0.00 0.00 0.00 4
    #
    # accuracy 0.62 609
    # macro avg 0.38 0.40 0.39 609
    # weighted avg 0.68 0.62 0.64 609

    # TEST #2 ~ 25% accuracy
    # Accuracy: 0.2447
    # F1-Score: 0.0962
    # Classification Report:
    #
    # precision recall f1-score support
    # 0 0.00 0.00 0.00 418
    # 1 0.00 0.00 0.00 407
    # 2 0.00 0.00 0.00 416
    # 3 0.24 1.00 0.39 402
    #
    # accuracy 0.24 1643
    # macro avg 0.06 0.25 0.10 1643
    # weighted avg 0.06 0.24 0.10 1643

    # TEST #3 ~ 30% accuracy
    # Accuracy: 0.3001
    # F1-Score: 0.2369
    # Classification Report:
    #
    # precision recall f1-score support
    # 0 0.27 0.73 0.40 418

```

```

#           1      0.00      0.00      0.00      407
#           2      0.37      0.30      0.33      416
#           3      0.34      0.16      0.22      402
#
#       accuracy                      0.30      1643
#   macro avg      0.25      0.30      0.24      1643
# weighted avg      0.25      0.30      0.24      1643

# OLD Model A:
# - Accuracy: 0.3774
# - F1-Score: 0.3484
# Classification Report:
#      precision    recall  f1-score   support
#           0       0.40     0.69      0.51      418
#           1       0.21     0.30      0.25      407
#           2       0.27     0.04      0.07      416
#           3       0.71     0.48      0.57      402
#       accuracy                      0.38      1643
#   macro avg      0.40      0.38      0.35      1643
# weighted avg      0.40      0.38      0.35      1643

# OLD Model A:
# - Accuracy: 0.2447
# - F1-Score: 0.0962
# Classification Report:
#      precision    recall  f1-score   support
#           0       0.00     0.00      0.00      418
#           1       0.00     0.00      0.00      407
#           2       0.00     0.00      0.00      416
#           3       0.24     1.00      0.39      402
#       accuracy                      0.24      1643
#   macro avg      0.06      0.25      0.10      1643
# weighted avg      0.06      0.24      0.10      1643

# Model A: Sequential Model with a Single Hidden Layer
# Model A: Sequential Model with Multiple Hidden Layers for Stability
# Previous Performance (Baseline Model A):
# - Accuracy: 0.5362
# - F1-Score: 0.5498
# Classification Report:
#      precision    recall  f1-score   support
#           0       0.50     0.72      0.59      418
#           1       0.26     0.35      0.30      407
#           2       0.96     0.38      0.54      416
#           3       0.87     0.70      0.77      402
#       accuracy                      0.54      1643
#   macro avg      0.65      0.54      0.55      1643

```

```

# weighted avg      0.65      0.54      0.55      1643
# Enhanced Model A: Improved Regularization and Learning Rate
↳Adjustments

# New Model A: Enhanced baseline with additional hidden layers
inputs = Input(shape=(input_shape,))
# Architecture A: 3 hidden layers with 128, 64, and 32 neurons
x = Dense(128, activation='relu', kernel_regularizer=l2(0.001))(inputs)
x = Dense(64, activation='relu', kernel_regularizer=l2(0.001))(x)
#x = LSTM(16, return_sequences=True)(x)
#x = Dense(32, activation='relu', kernel_regularizer=l2(0.001))(x)
x = Dense(32, activation='relu', kernel_regularizer=l2(0.001))(x)

outputs = Dense(4, activation='softmax')(x) # Output layer for 4
↳classes

# Create the model
model = Model(inputs=inputs, outputs=outputs)

# Compile the model with a standard loss function
optimizer = Adam(learning_rate=0.001)
model.compile(optimizer=optimizer, loss=CategoricalCrossentropy(),
↳metrics=['accuracy'])

elif architecture == 'B':
    # OLD Model B - Previous architectures and classification reports
    # TEST #1 ~ 68% accuracy
    # Accuracy: 0.6552
    # F1-Score: 0.5218
    # Classification Report:
    # precision      recall   f1-score   support
    # 0       0.66     1.00     0.79      401
    # 1       0.00     0.00     0.00      154
    # 2       0.00     0.00     0.00       50
    # 3       0.00     0.00     0.00        4
    #
    # accuracy           0.66      609
    # macro avg       0.16     0.25     0.20      609
    # weighted avg    0.43     0.66     0.52      609

    # TEST #2 ~ 25% accuracy
    # Accuracy: 0.2532
    # F1-Score: 0.1023
    # Classification Report:
    # precision      recall   f1-score   support
    # 0       0.00     0.00     0.00      418
    # 1       0.00     0.00     0.00      407

```

```

#          2      0.25    1.00    0.40    416
#          3      0.00    0.00    0.00    402
#
#      accuracy
#      macro avg     0.06    0.25    0.10    1643
# weighted avg     0.06    0.25    0.10    1643

# TEST #3 ~ 29% accuracy
# Accuracy: 0.2879
# F1-Score: 0.1912
# Classification Report:
#              precision    recall   f1-score   support
#          0      0.27    0.73    0.40    418
#          1      0.00    0.00    0.00    407
#          2      0.32    0.40    0.36    416
#          3      0.00    0.00    0.00    402
#
#      accuracy
#      macro avg     0.15    0.28    0.19    1643
# weighted avg     0.15    0.29    0.19    1643

# OLD Model B:
# - Accuracy: 0.2672
# - F1-Score: 0.1807
# Classification Report:
#              precision    recall   f1-score   support
#          0      0.30    0.72    0.43    418
#          1      0.00    0.00    0.00    407
#          2      0.03    0.01    0.01    416
#          3      0.25    0.33    0.28    402
#      accuracy
#      macro avg     0.14    0.27    0.18    1643
# weighted avg     0.14    0.27    0.18    1643

# OLD Model B:
# - Accuracy: 0.2465
# - F1-Score: 0.1005
# Classification Report:
#              precision    recall   f1-score   support
#          0      0.00    0.00    0.00    418
#          1      0.00    0.00    0.00    407
#          2      0.17    0.01    0.01    416
#          3      0.25    1.00    0.40    402
#      accuracy
#      macro avg     0.10    0.25    0.10    1643
# weighted avg     0.10    0.25    0.10    1643

```

```

# Model B: Functional Model with CNN-LSTM and Multi-Head Attention
# Previous Performance (Overfitting Model B):
# - Accuracy: 0.9884
# - F1-Score: 0.9884
# Classification Report:
#      precision    recall   f1-score   support
#      0       0.99    0.99    0.99     418
#      1       0.97    0.98    0.98     407
#      2       0.99    0.98    0.99     416
#      3       1.00    1.00    1.00     402
#   accuracy          0.99    0.99    0.99    1643
#   macro avg       0.99    0.99    0.99    1643
# weighted avg     0.99    0.99    0.99    1643

# New Model B: Reduced complexity with fewer attention heads and dense layers
inputs = Input(shape=(input_shape,))
reshaped = Reshape((input_shape, 1))(inputs) # Reshape for 1D Conv
x = Dense(128, activation='relu', kernel_regularizer=l2(0.001))(reshaped)
x = Conv1D(8, kernel_size=3, activation='relu', padding='same')(x)
x = LSTM(16, return_sequences=True)(x) # LSTM to capture sequence info

# Define query and value tensors for Multi-Head Attention
query = Dense(32)(x) # Define the query tensor
value = Dense(32)(x) # Define the value tensor

# Use Multi-Head Attention with query and value tensors
attention_output = MultiHeadAttention(num_heads=2, key_dim=32)(query=query, value=value)

# Pool the attention output and add the final dense layer
pooled_output = GlobalAveragePooling1D()(attention_output)
x = Dropout(0.3)(pooled_output)
outputs = Dense(4, activation='softmax')(x) # Output layer for 4 classes

# Create the model
model = Model(inputs=inputs, outputs=outputs)

# Compile the model with a standard loss function
optimizer = Adam(learning_rate=0.0004) # Reduced learning rate to control overfitting
model.compile(optimizer=optimizer, loss=CategoricalCrossentropy(), metrics=['accuracy'])

```

```

    else:
        raise ValueError("Unsupported architecture specified. Choose 'A' or 'B'.
        ↵")
    return model

# Create models for each architecture type
teacher_model_A = create_teacher_model(architecture='A',
    ↵input_shape=teacher_features.shape[1])
teacher_model_B = create_teacher_model(architecture='B',
    ↵input_shape=teacher_features.shape[1])

# Print the summaries of both models to verify architecture
print("Teacher Model A Summary:")
teacher_model_A.summary()

print("\nTeacher Model B Summary:")
teacher_model_B.summary()

```

Teacher Model A Summary:

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 102)	0
dense (Dense)	(None, 128)	13,184
dense_1 (Dense)	(None, 64)	8,256
dense_2 (Dense)	(None, 32)	2,080
dense_3 (Dense)	(None, 4)	132

Total params: 23,652 (92.39 KB)

Trainable params: 23,652 (92.39 KB)

Non-trainable params: 0 (0.00 B)

Teacher Model B Summary:

Model: "functional_1"

Layer (type)	Output Shape	Param #	Connected to
input_layer_3 (InputLayer)	(None, 102)	0	-
reshape (Reshape)	(None, 102, 1)	0	input_layer_3[0]...
dense_4 (Dense)	(None, 102, 128)	256	reshape[0] [0]
conv1d (Conv1D)	(None, 102, 8)	3,080	dense_4[0] [0]
lstm (LSTM)	(None, 102, 16)	1,600	conv1d[0] [0]
dense_5 (Dense)	(None, 102, 32)	544	lstm[0] [0]
dense_6 (Dense)	(None, 102, 32)	544	lstm[0] [0]
multi_head_attention (MultiHeadAttention)	(None, 102, 32)	8,416	dense_5[0] [0], dense_6[0] [0]
global_average_pooling2d (GlobalAveragePooling2D)	(None, 32)	0	multi_head_attention[0] [0]
dropout_1 (Dropout)	(None, 32)	0	global_average_pooling2d[0] [0]
dense_7 (Dense)	(None, 4)	132	dropout_1[0] [0]

Total params: 14,572 (56.92 KB)

Trainable params: 14,572 (56.92 KB)

Non-trainable params: 0 (0.00 B)

```
[80]: # Import necessary libraries
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.callbacks import EarlyStopping
import matplotlib.pyplot as plt
from sklearn.utils.class_weight import compute_class_weight
```

```

# Split the data into training and validation sets (already balanced using
# SMOTE earlier)
X_train, X_val, y_train, y_val = train_test_split(teacher_features,
                                                teacher_target, test_size=0.2, random_state=42)

print(X_train)
# Configure training hyperparameters
batch_size = 64
epochs = 50
learning_rate = 0.001

# Create the teacher model (choose architecture A or B)
teacher_model = teacher_model_A

# Ensure that y_train and y_val are converted to NumPy arrays before flattening
# or processing
y_train_np = y_train.values # Convert to NumPy array
y_val_np = y_val.values # Convert to NumPy array

# Print shapes of the features and target to ensure they are correct
print(f"X_train shape: {X_train.shape}")
print(f"X_val shape: {X_val.shape}")
print(f"y_train shape: {y_train_np.shape}")
print(f"y_val shape: {y_val_np.shape}")

# Check the data types and unique values in y_train and y_val to ensure they
# are categorical
print(f"y_train data type: {y_train_np.dtype}, unique values: {set(y_train_np.
# flatten())}")
print(f"y_val data type: {y_val_np.dtype}, unique values: {set(y_val_np.
# flatten())}")

# One-hot encode the labels using to_categorical if not already one-hot encoded
y_train_categorical = to_categorical(y_train_np, num_classes=4)
y_val_categorical = to_categorical(y_val_np, num_classes=4)

# Print the shapes after encoding to ensure everything is correct
print(f"y_train_categorical shape: {y_train_categorical.shape}")
print(f"y_val_categorical shape: {y_val_categorical.shape}")

# Ensure that the model is compiled with the appropriate loss and metrics
teacher_model = teacher_model_A # Choose the appropriate model

teacher_model.compile(
    optimizer='adam', # or any other optimizer of your choice

```

```

        loss='categorical_crossentropy', # Use categorical_crossentropy since
        ↪labels are one-hot encoded
        metrics=['accuracy'] # Monitor accuracy during training
    )

# Compute class weights
class_weights = compute_class_weight(
    class_weight='balanced',
    classes=np.unique(y_train_np),
    y=y_train_np
)

# Convert to dictionary format
class_weight_dict = dict(enumerate(class_weights))

# Remove or update the early stopping callback to monitor a valid metric
early_stopping = EarlyStopping(monitor='val_loss', patience=8,
    ↪restore_best_weights=True) # Updated patience to 4 as requested

# Train the teacher model
history = teacher_model.fit(
    X_train, y_train_categorical, # Use the one-hot encoded labels for training
    validation_data=(X_val, y_val_categorical),
    epochs=epochs,
    batch_size=batch_size,
    callbacks=[early_stopping],
    class_weight=class_weight_dict, # Apply class weights here
    verbose=1
)

# Plot training and validation loss
plt.figure(figsize=(10, 5))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Teacher Model Training & Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

# Evaluate the teacher model on the validation set
teacher_val_predictions = teacher_model.predict(X_val)
teacher_val_pred_labels = teacher_val_predictions.argmax(axis=1) # Convert
    ↪probabilities to class labels

# Print evaluation metrics
print("Teacher Model Performance on Validation Set:")

```

```

print(f"Accuracy: {accuracy_score(y_val_np, teacher_val_pred_labels):.4f}")
print(f"F1-Score: {f1_score(y_val_np, teacher_val_pred_labels, u
    ↪average='weighted'): .4f}")
print(f"Classification Report:\n{classification_report(y_val_np, u
    ↪teacher_val_pred_labels)}")

teacher_val_preds = teacher_model_A.predict(X_val)

```

	Basic_Demos-Enroll_Season	Basic_Demos-Age	Basic_Demos-Sex	\
4700	0.502580	7.565392	0.000000	
1181	0.598983	14.000000	1.000000	
1375	0.475815	15.000000	0.000000	
5787	0.503763	9.907644	0.226911	
2115	0.460940	9.604295	0.367842	
...	
5734	0.536519	13.275019	0.000000	
5191	0.477339	13.981799	0.000000	
5390	0.541954	12.000000	0.027975	
860	0.559547	8.000000	0.000000	
7270	0.500848	15.103731	0.367910	
	CGAS-Season	CGAS-CGAS_Score	Physical-Season	Physical-BMI
4700	0.515994	61.738432	0.518235	16.694711
1181	0.581124	60.000000	0.523758	20.732314
1375	0.515994	65.000000	0.516702	22.967517
5787	0.515994	66.546178	0.525762	19.552118
2115	0.460940	65.102546	0.471466	18.495364
...
5734	0.569345	64.375094	0.580097	19.951395
5191	0.539074	67.908993	0.525172	17.364689
5390	0.528603	62.776202	0.526350	20.241677
860	0.527092	80.000000	0.526350	17.758884
7270	0.534173	68.735820	0.491659	19.287629
	Physical-Height	Physical-Weight	Physical-Waist_Circumference	\
4700	51.630784	63.409656		20.390689
1181	62.500000	115.200000		28.473320
1375	75.250000	185.000000		35.152447
5787	56.382565	91.823578		26.835510
2115	54.579849	82.240167		26.032637
...
5734	69.431245	136.849510		31.374684
5191	69.254550	118.473234		28.084724
5390	57.139874	94.019621		40.339213
860	51.500000	67.000000		27.150807
7270	60.229286	101.171800		27.613246

	Physical-Diastolic_BP	Physical-HeartRate	Physical-Systolic_BP	\
4700	63.086520	82.565392	110.217304	
1181	56.000000	66.000000	95.000000	
1375	64.000000	81.000000	136.000000	
5787	60.092356	86.000000	111.680733	
2115	68.984227	82.140101	116.171643	
...	
5734	73.599699	84.424755	124.499623	
5191	62.291221	75.236617	110.364026	
5390	59.671394	75.664303	110.727343	
860	74.000000	89.000000	132.000000	
7270	72.992900	86.798660	120.941474	
 Fitness_Endurance-Season Fitness_Endurance-Max_Stage \				
4700	0.450653		4.246104	
1181	0.562024		5.045249	
1375	0.562024		2.585017	
5787	0.449568		5.040249	
2115	0.562024		5.022398	
...	
5734	0.562024		4.524442	
5191	0.562024		4.237524	
5390	0.420630		5.000368	
860	0.416561		6.000000	
7270	0.562024		4.817933	
 Fitness_Endurance-Time_Mins Fitness_Endurance-Time_Sec FGC-Season \				
4700	6.249104		18.435388	0.532606
1181	7.281378		27.478715	0.552717
1375	12.795107		36.652067	0.531007
5787	7.492937		25.325949	0.538366
2115	7.641242		26.788222	0.472214
...
5734	8.162711		20.767827	0.548770
5191	10.583830		21.916051	0.538627
5390	6.975520		41.548811	0.539792
860	9.000000		35.000000	0.539792
7270	7.042091		23.761783	0.538891
 FGC-FGC CU FGC-FGC CU_Zone FGC-FGC GSND FGC-FGC GSND_Zone \				
4700	7.826960	0.782696	18.176607	2.211874
1181	16.763021	0.351448	22.147415	1.827399
1375	18.000000	0.000000	22.200000	1.000000
5787	14.213739	0.753985	20.318358	2.133178
2115	11.067916	0.525539	18.121700	1.823866
...
5734	24.676073	0.275019	28.360045	2.000000
5191	64.962526	0.981799	30.056317	2.000000

5390	3.195823	0.000000	16.510481	1.972025		\
860	10.000000	1.000000	14.991645	1.789701		
7270	25.190724	0.698734	22.647991	1.654444		
4700	FGC-FGC_GSD	FGC-FGC_GSD_Zone	FGC-FGC_PU	FGC-FGC_PU_Zone	FGC-FGC_SRL	\
1181	13.077850	1.426754	5.565392	1.000000	11.217304	
1375	22.270642	2.093320	9.518281	0.475742	9.062625	
5787	49.600000	3.000000	9.000000	0.000000	7.783728	
2115	18.001850	2.129147	8.115063	0.616528	10.238470	
...	
5734	17.314493	2.016925	5.842512	0.360343	8.892884	
5191	28.287622	2.000000	6.375094	0.000000	3.624906	
5390	15.344051	1.972025	3.888101	0.000000	7.055949	
860	14.107620	2.297390	0.000000	0.000000	8.500000	
7270	20.886962	1.550619	8.923425	0.464942	8.657967	
4700	FGC-FGC_SRL_Zone	FGC-FGC_SRR	FGC-FGC_SRR_Zone	FGC-FGC_TL		\
1181	1.000000	12.000000	1.000000	9.782696		
1375	0.578585	9.036522	0.570378	10.257168		
5787	0.608529	8.536847	0.702746	8.000000		
2115	0.718168	10.341462	0.779268	8.868513		
...	
5734	0.678605	9.004501	0.680599	9.016459		
5191	0.000000	4.349887	0.000000	8.724981		
5390	0.000000	0.109208	0.000000	8.018201		
860	0.000000	6.569937	0.000000	8.055949		
7270	1.000000	7.500000	1.000000	8.000000		
	0.336244	8.679490	0.419282	9.572363		
4700	FGC-FGC_TL_Zone	BIA-Season	BIA-BIA_Activity_Level_num	BIA-BIA_BMC		\
1181	1.000000	0.566098	3.000000	3.317999		
1375	0.726999	0.490251	3.000127	7.660636		
5787	0.000000	0.566098	3.000000	8.322940		
2115	0.631474	0.563331	2.773089	4.139876		
...	
5734	0.772281	0.490251	2.687674	7.660624		
5191	0.724981	0.542911	3.000000	6.642455		
5390	0.018201	0.565516	3.000000	6.410864		
860	0.027975	0.534475	1.972025	9.755144		
7270	1.000000	0.534475	4.000000	7.134250		
	0.777310	0.506521	2.728329	5.298298		
4700	BIA-BIA_BMI	BIA-BIA_BMR	BIA-BIA_DEE	BIA-BIA_ECW	BIA-BIA_FFM	\
1181	16.696570	1035.152246	1759.756600	11.941833	52.520217	
1375	18.540285	1229.030094	2084.783491	20.415851	73.170816	
5787	22.970000	1863.730000	3168.330000	44.472800	140.774000	
	19.554283	1192.572076	1960.892484	20.535850	69.287832	

2115	18.540302	1229.029946	2055.943863	20.415803	73.170848	
...	
5734	19.953576	1560.797970	2653.357374	33.209356	108.508055	
5191	17.366620	1475.213996	2507.866739	29.309628	99.392644	
5390	20.243845	1160.136643	1845.637392	16.047988	65.832307	
860	17.760800	1029.600000	2162.150000	11.490600	51.928600	
7270	19.763566	1276.004739	2080.516891	23.732340	78.174404	
	BIA-BIA_FFMI	BIA-BIA_FMI	BIA-BIA_Fat	BIA-BIA_Frame_num	BIA-BIA_ICW	\
4700	13.829303	2.867249	10.889446	1.000000	27.850559	
1181	14.810861	3.729442	38.333226	1.823437	32.828975	
1375	17.478900	5.491160	44.225700	3.000000	58.332500	
5787	15.097468	4.456760	22.535746	2.000000	32.374804	
2115	14.810861	3.729442	9.164517	1.663348	32.829002	
...	
5734	15.822819	4.130711	28.341166	1.724981	46.512153	
5191	14.569769	2.796792	19.080583	1.018201	43.256442	
5390	14.174343	6.069581	28.187314	1.972025	30.204337	
860	13.765600	3.995230	15.071400	2.000000	26.351600	
7270	14.928128	4.835409	23.609686	1.678369	33.655141	
	BIA-BIA_LDM	BIA-BIA_LST	BIA-BIA_SMM	BIA-BIA_TBW	PAQ_A-Season	\
4700	12.727817	49.202221	24.608922	39.792399	0.480263	
1181	19.926072	65.510248	42.408203	53.244832	0.480263	
1375	37.969000	132.451000	65.539300	102.805000	0.867459	
5787	16.377178	65.147995	30.339432	52.910654	0.480263	
2115	19.926029	65.510205	33.972700	53.244809	0.480263	
...	
5734	28.786835	101.866013	47.542115	79.721509	0.603595	
5191	26.826581	92.981790	44.731676	72.566070	0.920551	
5390	19.579983	56.077124	25.595848	46.252325	0.480263	
860	14.086400	44.794300	20.822800	37.842200	0.480263	
7270	20.786931	72.876101	34.943804	57.387476	0.649018	
	PAQ_A-PAQ_A_Total	PAQ_C-Season	PAQ_C-PAQ_C_Total	PCIAT-PCIAT_Total		\
4700	1.920678	0.526024	2.475277	51.000000		
1181	2.185024	0.579612	2.640000	27.000000		
1375	4.309000	0.460443	-37.127996	13.000000		
5787	2.019716	0.610596	3.053284	54.773089		
2115	2.101212	0.460443	2.540356	8.770492		
...	
5734	2.429442	0.588854	-2.360806	58.550038		
5191	3.044169	0.463667	-10.972151	59.963597		
5390	1.859503	0.549041	1.637975	57.832152		
860	2.203806	0.460443	2.703067	20.000000		
7270	1.735669	0.513405	5.289773	81.000000		
	SDS-Season	SDS-SDS_Total_Raw	SDS-SDS_Total_T	PreInt_EduHx-Season		\

4700	0.518336	67.434608	91.651912	0.511340
1181	0.611293	46.000000	64.000000	0.602178
1375	0.512539	31.000000	45.000000	0.486120
5787	0.539217	31.361466	44.815288	0.512454
2115	0.467407	40.896130	57.473724	0.457262
...
5734	0.584134	31.300226	45.125282	0.542743
5191	0.514336	39.781584	55.726980	0.487541
5390	0.515378	46.055949	64.083924	0.532693
860	0.515460	45.000000	63.000000	0.564223
7270	0.513613	51.471641	71.207461	0.503747

	PreInt_EduHx-computerinternet_hoursday	Age_Group	PCIAT_Cluster	\
4700		0.217304	0.362030	4.869216
1181		3.000000	0.855589	0.000000
1375		0.000000	0.855589	0.000000
5787		1.226911	0.474024	4.000000
2115		0.695464	0.443345	0.000000
...
5734		1.449962	0.855589	8.275019
5191		0.036403	0.855589	8.981799
5390		2.000000	0.855589	4.111899
860		0.000000	0.362030	0.000000
7270		2.000000	0.899069	8.000000

	CGAS-CGAS_Score_x SDS-SDS_Total_Raw	CGAS-CGAS_Score_x_Physical-BMI	\
4700	4166.028261	1030.154161	
1181	2760.000000	1243.938816	
1375	2015.000000	1492.888599	
5787	2084.880616	1297.875366	
2115	2645.540688	1204.515066	
...
5734	2026.918002	1280.724352	
5191	2702.599551	1178.891546	
5390	2890.782516	1270.780770	
860	3600.000000	1420.710718	
7270	3539.805865	1329.224327	

	X_mean	X_std	X_min	X_max	Y_mean	Y_std	Y_min	\
4700	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
1181	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
1375	0.059223	0.119636	-0.949533	1.042885	0.160075	0.413583	-0.997729	
5787	-0.264147	0.586831	-2.053381	1.867559	-0.001036	0.448261	-2.929571	
2115	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
...	
5734	-0.016970	0.305961	-1.571900	1.315234	0.028214	0.297028	-2.764179	
5191	0.027425	0.095131	-0.970502	1.002803	0.042165	0.162715	-1.039631	
5390	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	

860	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
7270	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	Y_max	Z_mean	Z_std	Z_min	Z_max	enmo_mean	enmo_std	\
4700	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
1181	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
1375	1.035902	-0.621916	0.653727	-1.023129	1.013462	0.015610	0.009221	
5787	2.699965	-0.067758	0.559380	-1.011406	1.623062	0.036143	0.126210	
2115	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
...
5734	2.026787	-0.518336	0.595110	-1.020474	1.045226	0.018623	0.064642	
5191	1.023706	-0.950779	0.188632	-1.014648	0.980170	0.001053	0.006825	
5390	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
860	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
7270	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	anglez_mean	anglez_std	non-wear_flag_mean	light_mean	light_std	\		
4700	0.000000	0.000000		0.000000	0.000000	0.000000		
1181	0.000000	0.000000		0.000000	0.000000	0.000000		
1375	-53.168716	51.672413		0.908472	11.131063	17.960384		
5787	-4.987710	40.240898		0.036958	28.955147	143.626431		
2115	0.000000	0.000000		0.000000	0.000000	0.000000		
...		
5734	-44.395025	50.065777		0.586121	10.875281	41.560736		
5191	-83.972223	17.170857		0.903722	6.160095	59.511204		
5390	0.000000	0.000000		0.000000	0.000000	0.000000		
860	0.000000	0.000000		0.000000	0.000000	0.000000		
7270	0.000000	0.000000		0.000000	0.000000	0.000000		
	battery_voltage_mean	battery_voltage_std	time_of_day_mean	\				
4700	0.000000		0.000000	0.000000e+00				
1181	0.000000		0.000000	0.000000e+00				
1375	3844.954346		163.499146	4.315404e+13				
5787	3845.312609		159.261820	4.328247e+13				
2115	0.000000		0.000000	0.000000e+00				
...				
5734	3854.832900		164.385136	4.323829e+13				
5191	3856.278209		162.648632	4.323598e+13				
5390	0.000000		0.000000	0.000000e+00				
860	0.000000		0.000000	0.000000e+00				
7270	0.000000		0.000000	0.000000e+00				
	weekday_mean	quarter_mean	relative_date_PCIAT_mean	fourier_X_real	\			
4700	0.000000	0.000000		0.000000	0.000000			
1181	0.000000	0.000000		0.000000	0.000000			
1375	4.186077	2.905743		18.562656	1548.397978			
5787	4.007968	3.546178		149.066992	-42939.590174			
2115	0.000000	0.000000		0.000000	0.000000			

...
5734	4.187859	1.716959	54.741550	10162.399097
5191	4.204346	3.559497	111.615809	-308.758777
5390	0.000000	0.000000	0.000000	0.000000
860	0.000000	0.000000	0.000000	0.000000
7270	0.000000	0.000000	0.000000	0.000000
...
4700	0.000000e+00	0.000000	0.000000	0.000000
1181	0.000000e+00	0.000000	0.000000	0.000000
1375	3.637979e-13	17745.827957	0.000000	-16342.842688
5787	-6.858480e-13	801.332181	184.197653	-8737.058914
2115	0.000000e+00	0.000000	0.000000	0.000000
...
5734	-2.917840e+03	3456.750701	291.801908	-59359.227833
5191	-7.325500e+01	8149.463251	7.325950	-70943.255998
5390	0.000000e+00	0.000000	0.000000	0.000000
860	0.000000e+00	0.000000	0.000000	0.000000
7270	0.000000e+00	0.000000	0.000000	0.000000
...
4700	0.000000e+00	0.0	0.000000	
1181	0.000000e+00	0.0	0.000000	
1375	5.820766e-12	0.0	6689.417480	
5787	-2.446071e+03	0.0	14316.060811	
2115	0.000000e+00	0.0	0.000000	
...
5734	3.488591e-13	0.0	8078.098284	
5191	3.634228e-13	0.0	446.840576	
5390	0.000000e+00	0.0	0.000000	
860	0.000000e+00	0.0	0.000000	
7270	0.000000e+00	0.0	0.000000	
...
4700	activity_ratio_day_night	non_wear_proportion	sedentary_proportion	\
1181	0.0	0.000000	0.000000	
1375	0.0	0.000000	0.000000	
5787	0.0	0.908472	0.995669	
2115	0.0	0.036958	0.859015	
...
5734	0.0	0.586121	0.919501	
5191	0.0	0.903722	0.996632	
5390	0.0	0.000000	0.000000	
860	0.0	0.000000	0.000000	
7270	0.0	0.000000	0.000000	
...
4700	light_activity_proportion	moderate_activity_proportion	\	
1181	0.000000	0.000000		

```

1181          0.000000          0.000000
1375          0.004329          0.000002
5787          0.129437          0.007394
2115          0.000000          0.000000
...
           ...
5734          0.077019          0.002208
5191          0.003271          0.000065
5390          0.000000          0.000000
860           0.000000          0.000000
7270          0.000000          0.000000

    vigorous_activity_proportion
4700          0.000000
1181          0.000000
1375          0.000000
5787          0.004154
2115          0.000000
...
           ...
5734          0.001271
5191          0.000032
5390          0.000000
860           0.000000
7270          0.000000

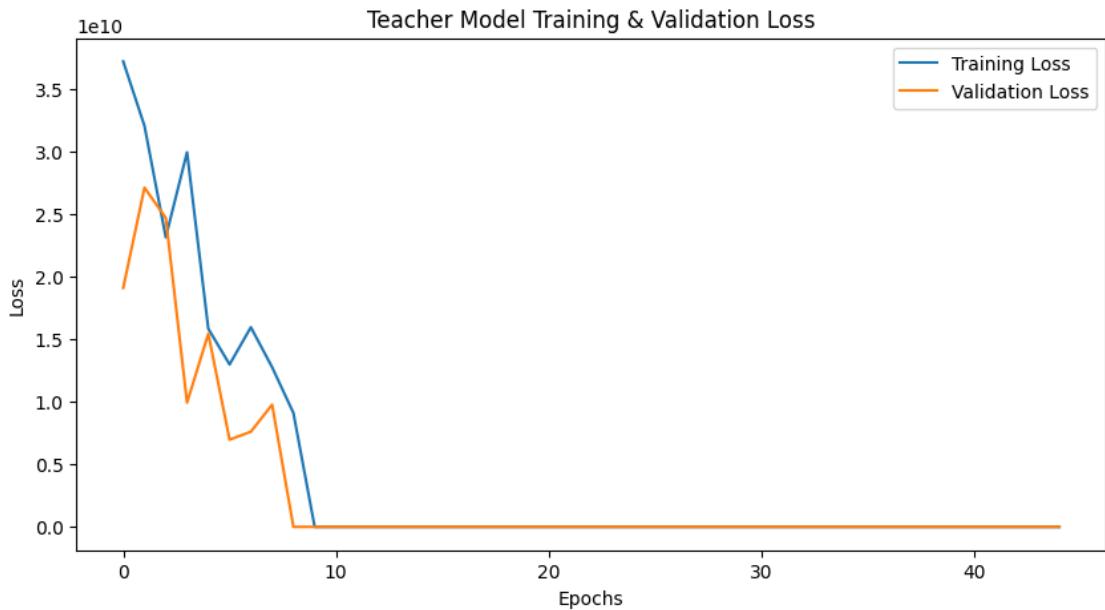
[6569 rows x 102 columns]
X_train shape: (6569, 102)
X_val shape: (1643, 102)
y_train shape: (6569,)
y_val shape: (1643,)
y_train data type: int64, unique values: {0, 1, 2, 3}
y_val data type: int64, unique values: {0, 1, 2, 3}
y_train_categorical shape: (6569, 4)
y_val_categorical shape: (1643, 4)
Epoch 1/50
103/103      2s 4ms/step -
accuracy: 0.4369 - loss: 50564001792.0000 - val_accuracy: 0.4419 - val_loss:
19116826624.0000
Epoch 2/50
103/103      0s 2ms/step -
accuracy: 0.4420 - loss: 34283069440.0000 - val_accuracy: 0.4437 - val_loss:
27138234368.0000
Epoch 3/50
103/103      0s 2ms/step -
accuracy: 0.5087 - loss: 21594140672.0000 - val_accuracy: 0.4784 - val_loss:
24713201664.0000
Epoch 4/50
103/103      0s 2ms/step -
accuracy: 0.5392 - loss: 31784050688.0000 - val_accuracy: 0.4912 - val_loss:

```

9934446592.0000
Epoch 5/50
103/103 0s 2ms/step -
accuracy: 0.5239 - loss: 20208961536.0000 - val_accuracy: 0.6336 - val_loss:
15447905280.0000
Epoch 6/50
103/103 0s 2ms/step -
accuracy: 0.5981 - loss: 13002493952.0000 - val_accuracy: 0.5247 - val_loss:
6976550912.0000
Epoch 7/50
103/103 0s 2ms/step -
accuracy: 0.5450 - loss: 15250896896.0000 - val_accuracy: 0.6409 - val_loss:
7611130880.0000
Epoch 8/50
103/103 0s 2ms/step -
accuracy: 0.5765 - loss: 12817714176.0000 - val_accuracy: 0.6494 - val_loss:
9775671296.0000
Epoch 9/50
103/103 0s 2ms/step -
accuracy: 0.6289 - loss: 13025772544.0000 - val_accuracy: 0.6738 - val_loss:
0.9720
Epoch 10/50
103/103 0s 2ms/step -
accuracy: 0.6812 - loss: 0.9475 - val_accuracy: 0.7127 - val_loss: 0.8914
Epoch 11/50
103/103 0s 2ms/step -
accuracy: 0.7152 - loss: 0.8489 - val_accuracy: 0.7365 - val_loss: 0.8106
Epoch 12/50
103/103 0s 2ms/step -
accuracy: 0.7550 - loss: 0.7769 - val_accuracy: 0.7419 - val_loss: 0.7919
Epoch 13/50
103/103 0s 2ms/step -
accuracy: 0.7519 - loss: 0.7780 - val_accuracy: 0.7529 - val_loss: 0.7728
Epoch 14/50
103/103 0s 2ms/step -
accuracy: 0.7530 - loss: 0.7633 - val_accuracy: 0.7389 - val_loss: 0.7977
Epoch 15/50
103/103 0s 2ms/step -
accuracy: 0.7429 - loss: 0.7767 - val_accuracy: 0.7492 - val_loss: 0.7557
Epoch 16/50
103/103 0s 2ms/step -
accuracy: 0.7373 - loss: 0.7771 - val_accuracy: 0.7407 - val_loss: 0.7703
Epoch 17/50
103/103 0s 2ms/step -
accuracy: 0.7528 - loss: 0.7400 - val_accuracy: 0.6391 - val_loss: 0.9627
Epoch 18/50
103/103 0s 2ms/step -
accuracy: 0.7267 - loss: 0.7951 - val_accuracy: 0.7553 - val_loss: 0.7473

```
Epoch 19/50
103/103      0s 2ms/step -
accuracy: 0.7625 - loss: 0.7289 - val_accuracy: 0.7578 - val_loss: 0.7279
Epoch 20/50
103/103      0s 2ms/step -
accuracy: 0.7549 - loss: 0.7363 - val_accuracy: 0.7596 - val_loss: 0.7279
Epoch 21/50
103/103      0s 2ms/step -
accuracy: 0.7636 - loss: 0.7157 - val_accuracy: 0.7614 - val_loss: 0.7247
Epoch 22/50
103/103      0s 2ms/step -
accuracy: 0.7654 - loss: 0.7074 - val_accuracy: 0.7389 - val_loss: 0.7648
Epoch 23/50
103/103      0s 2ms/step -
accuracy: 0.7522 - loss: 0.7291 - val_accuracy: 0.7395 - val_loss: 0.7697
Epoch 24/50
103/103      0s 2ms/step -
accuracy: 0.7385 - loss: 0.7564 - val_accuracy: 0.7529 - val_loss: 0.7278
Epoch 25/50
103/103      0s 2ms/step -
accuracy: 0.7536 - loss: 0.7208 - val_accuracy: 0.7675 - val_loss: 0.6954
Epoch 26/50
103/103      0s 2ms/step -
accuracy: 0.7570 - loss: 0.7128 - val_accuracy: 0.7602 - val_loss: 0.7077
Epoch 27/50
103/103      0s 2ms/step -
accuracy: 0.7625 - loss: 0.7021 - val_accuracy: 0.7529 - val_loss: 0.7084
Epoch 28/50
103/103      0s 2ms/step -
accuracy: 0.7573 - loss: 0.7023 - val_accuracy: 0.7681 - val_loss: 0.6909
Epoch 29/50
103/103      0s 2ms/step -
accuracy: 0.7512 - loss: 0.7244 - val_accuracy: 0.7590 - val_loss: 0.7083
Epoch 30/50
103/103      0s 2ms/step -
accuracy: 0.7394 - loss: 0.7494 - val_accuracy: 0.7304 - val_loss: 0.7666
Epoch 31/50
103/103      0s 2ms/step -
accuracy: 0.7663 - loss: 0.7054 - val_accuracy: 0.7626 - val_loss: 0.6941
Epoch 32/50
103/103      0s 2ms/step -
accuracy: 0.7606 - loss: 0.6994 - val_accuracy: 0.6963 - val_loss: 0.9199
Epoch 33/50
103/103      0s 2ms/step -
accuracy: 0.7139 - loss: 0.8451 - val_accuracy: 0.7645 - val_loss: 0.6888
Epoch 34/50
103/103      0s 2ms/step -
accuracy: 0.7648 - loss: 0.7026 - val_accuracy: 0.7371 - val_loss: 0.7481
```

```
Epoch 35/50
103/103      0s 2ms/step -
accuracy: 0.7585 - loss: 0.7193 - val_accuracy: 0.6275 - val_loss: 1.0134
Epoch 36/50
103/103      0s 2ms/step -
accuracy: 0.7183 - loss: 0.8031 - val_accuracy: 0.7687 - val_loss: 0.6738
Epoch 37/50
103/103      0s 2ms/step -
accuracy: 0.7751 - loss: 0.6666 - val_accuracy: 0.7718 - val_loss: 0.6642
Epoch 38/50
103/103      0s 2ms/step -
accuracy: 0.7667 - loss: 0.6746 - val_accuracy: 0.7614 - val_loss: 0.6877
Epoch 39/50
103/103      0s 2ms/step -
accuracy: 0.7677 - loss: 0.6771 - val_accuracy: 0.7273 - val_loss: 0.7783
Epoch 40/50
103/103      0s 2ms/step -
accuracy: 0.7620 - loss: 0.7038 - val_accuracy: 0.7541 - val_loss: 0.7097
Epoch 41/50
103/103      0s 2ms/step -
accuracy: 0.7567 - loss: 0.6888 - val_accuracy: 0.7438 - val_loss: 0.7402
Epoch 42/50
103/103      0s 2ms/step -
accuracy: 0.7520 - loss: 0.6994 - val_accuracy: 0.7663 - val_loss: 0.6777
Epoch 43/50
103/103      0s 2ms/step -
accuracy: 0.7211 - loss: 1.1159 - val_accuracy: 0.7365 - val_loss: 1.3660
Epoch 44/50
103/103      0s 2ms/step -
accuracy: 0.7394 - loss: 0.8639 - val_accuracy: 0.7048 - val_loss: 0.8435
Epoch 45/50
103/103      0s 2ms/step -
accuracy: 0.7344 - loss: 0.7639 - val_accuracy: 0.6939 - val_loss: 0.8696
```



52/52 0s 2ms/step

Teacher Model Performance on Validation Set:

Accuracy: 0.7718

F1-Score: 0.7853

Classification Report:

	precision	recall	f1-score	support
0	0.98	0.72	0.83	418
1	0.95	0.69	0.80	407
2	0.53	0.98	0.69	416
3	1.00	0.70	0.82	402
accuracy			0.77	1643
macro avg	0.87	0.77	0.79	1643
weighted avg	0.87	0.77	0.79	1643

52/52 0s 1ms/step

```
[58]: # training data preprocessing
# Import necessary libraries
import pandas as pd
import numpy as np
from scipy.stats import skew, kurtosis

# Step 2: Filter only the numeric columns from the test data
numeric_cols = test_df.select_dtypes(include=[np.number]).columns
```

```

# Step 3: Create a summary statistics DataFrame
summary_stats = test_df[numeric_cols].describe().T

# Step 4: Add skewness and kurtosis to the summary statistics DataFrame
summary_stats['Skewness'] = test_df[numeric_cols].apply(skew)
summary_stats['Kurtosis'] = test_df[numeric_cols].apply(kurtosis)

# Step 5: Identify potential outliers using the IQR method
Q1 = test_df[numeric_cols].quantile(0.25)
Q3 = test_df[numeric_cols].quantile(0.75)
IQR = Q3 - Q1
summary_stats['Lower_Bound'] = Q1 - 1.5 * IQR
summary_stats['Upper_Bound'] = Q3 + 1.5 * IQR

# Calculate the number of outliers for each column
summary_stats['Outliers'] = test_df[numeric_cols].apply(
    lambda x: ((x < summary_stats.loc[x.name, 'Lower_Bound']) |
                (x > summary_stats.loc[x.name, 'Upper_Bound'])).sum()
)

# Step 6: Display the summary statistics DataFrame
print("\nNumeric Feature Summary Analysis for Test Data:\n")
print(summary_stats)

# Step 7: Print skewness and kurtosis separately to understand distributions
print("\nSkewness of Numeric Features in Test Data:\n")
print(test_df[numeric_cols].apply(skew))

print("\nKurtosis of Numeric Features in Test Data:\n")
print(test_df[numeric_cols].apply(kurtosis))

```

Numeric Feature Summary Analysis for Test Data:

	count	mean	std	\
Basic_Demos-Age	20.0	10.750000	3.725799	
Basic_Demos-Sex	20.0	0.400000	0.502625	
CGAS-CGAS_Score	8.0	62.500000	11.275764	
Physical-BMI	13.0	19.835939	4.927625	
Physical-Height	13.0	52.961538	6.942357	
Physical-Weight	13.0	79.200000	23.632181	
Physical-Waist_Circumference	5.0	25.400000	3.130495	
Physical-Diastolic_BP	11.0	70.545455	18.806189	
Physical-HeartRate	12.0	81.666667	9.316001	
Physical-Systolic_BP	11.0	117.545455	21.262002	
Fitness_Endurance-Max_Stage	3.0	5.000000	1.000000	
Fitness_Endurance-Time_Mins	3.0	7.000000	2.000000	
Fitness_Endurance-Time_Sec	3.0	34.000000	2.645751	

FGC-FGC_CU	13.0	8.692308	7.899205
FGC-FGC_CU_Zone	13.0	0.461538	0.518875
FGC-FGC_G SND	5.0	16.160000	4.879857
FGC-FGC_G SND_Zone	5.0	1.600000	0.547723
FGC-FGC_G SD	5.0	16.740000	3.990363
FGC-FGC_G SD_Zone	5.0	1.600000	0.547723
FGC-FGC_PU	13.0	4.000000	5.627314
FGC-FGC_PU_Zone	13.0	0.153846	0.375534
FGC-FGC_S RL	13.0	7.500000	4.000000
FGC-FGC_S RL_Zone	13.0	0.538462	0.518875
FGC-FGC_S RR	13.0	7.961538	4.436879
FGC-FGC_S RR_Zone	13.0	0.615385	0.506370
FGC-FGC_T L	13.0	7.961538	3.152126
FGC-FGC_T L_Zone	13.0	0.692308	0.480384
BIA-BIA_Activity_Level_num	8.0	2.625000	1.060660
BIA-BIA_BMC	8.0	3.636360	0.898087
BIA-BIA_BMI	8.0	19.284788	4.876077
BIA-BIA_BMR	8.0	1111.248000	143.724879
BIA-BIA_DEE	8.0	1886.912500	486.140935
BIA-BIA_ECW	8.0	16.681051	7.651128
BIA-BIA_F FM	8.0	60.625612	15.308597
BIA-BIA_F FMI	8.0	14.432937	1.227543
BIA-BIA_F MI	8.0	4.851857	3.728203
BIA-BIA_F at	8.0	21.799390	19.920902
BIA-BIA_F rame_num	8.0	1.625000	0.517549
BIA-BIA_ICW	8.0	28.486750	5.099449
BIA-BIA_LDM	8.0	15.457795	4.021153
BIA-BIA_LST	8.0	56.989275	14.490362
BIA-BIA_SMM	8.0	25.985962	7.479799
BIA-BIA_TBW	8.0	45.167825	11.940000
PAQ_A-PAQ_A_Total	1.0	1.040000	NaN
PAQ_C-PAQ_C_Total	9.0	2.372333	1.080099
SDS-SDS_Total_Raw	10.0	36.800000	5.533735
SDS-SDS_Total_T	10.0	52.300000	7.024560
PreInt_EduHx-computerinternet_hoursday	16.0	1.437500	1.152895

	min	25%	50%	\
Basic_Demos-Age	5.000000	9.000000	10.000000	
Basic_Demos-Sex	0.000000	0.000000	0.000000	
CGAS-CGAS_Score	50.000000	51.000000	63.000000	
Physical-BMI	14.03559	16.861286	18.292347	
Physical-Height	37.50000	48.000000	55.000000	
Physical-Weight	46.00000	60.200000	81.600000	
Physical-Waist_Circumference	22.00000	24.000000	24.000000	
Physical-Diastolic_BP	57.00000	60.500000	63.000000	
Physical-HeartRate	70.00000	74.500000	80.000000	
Physical-Systolic_BP	95.00000	102.500000	116.000000	
Fitness_Endurance-Max_Stage	4.00000	4.500000	5.000000	

Fitness_Endurance-Time_Mins	5.00000	6.000000	7.000000
Fitness_Endurance-Time_Sec	32.00000	32.500000	33.000000
FGC-FGC_CU	0.00000	3.000000	6.000000
FGC-FGC_CU_Zone	0.00000	0.000000	0.000000
FGC-FGC_G SND	10.20000	12.600000	16.500000
FGC-FGC_G SND_Zone	1.00000	1.000000	2.000000
FGC-FGC_G SD	11.10000	14.700000	17.900000
FGC-FGC_G SD_Zone	1.00000	1.000000	2.000000
FGC-FGC_PU	0.00000	0.000000	2.000000
FGC-FGC_PU_Zone	0.00000	0.000000	0.000000
FGC-FGC_S RL	0.00000	7.000000	8.000000
FGC-FGC_S RL_Zone	0.00000	0.000000	1.000000
FGC-FGC_S RR	0.00000	6.000000	9.500000
FGC-FGC_S RR_Zone	0.00000	0.000000	1.000000
FGC-FGC_T L	3.00000	6.000000	7.000000
FGC-FGC_T L_Zone	0.00000	0.000000	1.000000
BIA-BIA_Activity_Level_num	2.00000	2.000000	2.000000
BIA-BIA_BMC	2.57949	2.729900	3.812310
BIA-BIA_BMI	14.03710	16.875175	17.784050
BIA-BIA_BMR	932.49800	986.466500	1133.645000
BIA-BIA_DEE	1492.00000	1503.120000	1852.720000
BIA-BIA_ECW	6.01993	13.423195	15.960000
BIA-BIA_F FM	41.58620	47.334825	63.011350
BIA-BIA_F FMI	12.82540	13.765575	14.081900
BIA-BIA_F MI	1.21172	3.153410	3.737140
BIA-BIA_F at	3.97085	10.625893	17.535850
BIA-BIA_F rame_num	1.00000	1.000000	2.000000
BIA-BIA_ICW	21.03520	24.230725	29.470400
BIA-BIA_LDM	8.89536	13.815400	16.402450
BIA-BIA_L ST	38.91770	44.627250	59.199050
BIA-BIA_S MM	15.41070	19.801775	26.337750
BIA-BIA_TB W	27.05520	37.245575	46.608850
PAQ_A-PAQ_A_Total	1.04000	1.040000	1.040000
PAQ_C-PAQ_C_Total	1.10000	1.270000	2.340000
SDS-SDS_Total_Raw	27.00000	33.500000	37.500000
SDS-SDS_Total_T	40.00000	47.750000	53.500000
PreInt_EduHx-computerinternet_hoursday	0.00000	0.000000	2.000000

	75%	max	Skewness	\
Basic_Demos-Age	12.250000	19.000000	0.514853	
Basic_Demos-Sex	1.000000	1.000000	0.408248	
CGAS-CGAS_Score	71.000000	80.000000	NaN	
Physical-BMI	21.079065	30.094649	NaN	
Physical-Height	57.750000	60.000000	NaN	
Physical-Weight	85.600000	121.600000	NaN	
Physical-Waist_Circumference	27.000000	30.000000	NaN	
Physical-Diastolic_BP	73.000000	123.000000	NaN	
Physical-HeartRate	90.250000	97.000000	NaN	

Physical-Systolic_BP	119.500000	163.000000	NaN
Fitness_Endurance-Max_Stage	5.500000	6.000000	NaN
Fitness_Endurance-Time_Mins	8.000000	9.000000	NaN
Fitness_Endurance-Time_Sec	35.000000	37.000000	NaN
FGC-FGC CU	12.000000	24.000000	NaN
FGC-FGC CU_Zone	1.000000	1.000000	NaN
FGC-FGC GSND	19.200000	22.300000	NaN
FGC-FGC GSND_Zone	2.000000	2.000000	NaN
FGC-FGC GSD	18.400000	21.600000	NaN
FGC-FGC GSD_Zone	2.000000	2.000000	NaN
FGC-FGC PU	6.000000	20.000000	NaN
FGC-FGC PU_Zone	0.000000	1.000000	NaN
FGC-FGC SRL	10.500000	12.000000	NaN
FGC-FGC SRL_Zone	1.000000	1.000000	NaN
FGC-FGC SRR	11.000000	15.000000	NaN
FGC-FGC SRR_Zone	1.000000	1.000000	NaN
FGC-FGC TL	11.000000	12.500000	NaN
FGC-FGC TL_Zone	1.000000	1.000000	NaN
BIA-BIA_Activity_Level_num	3.000000	5.000000	NaN
BIA-BIA_BMC	4.125535	5.080250	NaN
BIA-BIA_BMI	20.017525	30.186500	NaN
BIA-BIA_BMR	1194.895000	1330.970000	NaN
BIA-BIA_DEE	1941.692500	2974.710000	NaN
BIA-BIA_ECW	20.450875	30.212400	NaN
BIA-BIA_FFM	69.535100	84.028500	NaN
BIA-BIA_FFFI	14.939925	16.687700	NaN
BIA-BIA_FMI	5.077595	13.498800	NaN
BIA-BIA_Fat	22.444175	67.971500	NaN
BIA-BIA_Frame_num	2.000000	2.000000	NaN
BIA-BIA_ICW	31.398725	36.057200	NaN
BIA-BIA_LDM	17.674625	20.902000	NaN
BIA-BIA_LST	65.222050	79.698200	NaN
BIA-BIA_SMM	30.421100	36.223200	NaN
BIA-BIA_TBW	51.860475	63.126500	NaN
PAQ_A-PAQ_A_Total	1.040000	1.040000	NaN
PAQ_C-PAQ_C_Total	3.020000	4.110000	NaN
SDS-SDS_Total_Raw	39.750000	46.000000	NaN
SDS-SDS_Total_T	55.750000	64.000000	NaN
PreInt_EduHx-computerinternet_hoursday	2.000000	3.000000	NaN

	Kurtosis	Lower_Bound	Upper_Bound	\
Basic_Demos-Age	0.073754	4.125000	17.125000	
Basic_Demos-Sex	-1.833333	-1.500000	2.500000	
CGAS-CGAS_Score	NaN	21.000000	101.000000	
Physical-BMI	NaN	10.534618	27.405733	
Physical-Height	NaN	33.375000	72.375000	
Physical-Weight	NaN	22.100000	123.700000	
Physical-Waist_Circumference	NaN	19.500000	31.500000	

Physical-Diastolic_BP	NaN	41.750000	91.750000
Physical-HeartRate	NaN	50.875000	113.875000
Physical-Systolic_BP	NaN	77.000000	145.000000
Fitness_Endurance-Max_Stage	NaN	3.000000	7.000000
Fitness_Endurance-Time_Mins	NaN	3.000000	11.000000
Fitness_Endurance-Time_Sec	NaN	28.750000	38.750000
FGC-FGC CU	NaN	-10.500000	25.500000
FGC-FGC CU_Zone	NaN	-1.500000	2.500000
FGC-FGC GSND	NaN	2.700000	29.100000
FGC-FGC GSND_Zone	NaN	-0.500000	3.500000
FGC-FGC GSD	NaN	9.150000	23.950000
FGC-FGC GSD_Zone	NaN	-0.500000	3.500000
FGC-FGC PU	NaN	-9.000000	15.000000
FGC-FGC PU_Zone	NaN	0.000000	0.000000
FGC-FGC SRL	NaN	1.750000	15.750000
FGC-FGC SRL_Zone	NaN	-1.500000	2.500000
FGC-FGC SRR	NaN	-1.500000	18.500000
FGC-FGC SRR_Zone	NaN	-1.500000	2.500000
FGC-FGC TL	NaN	-1.500000	18.500000
FGC-FGC TL_Zone	NaN	-1.500000	2.500000
BIA-BIA_Activity_Level_num	NaN	0.500000	4.500000
BIA-BIA_BMC	NaN	0.636448	6.218987
BIA-BIA_BMI	NaN	12.161650	24.731050
BIA-BIA_BMR	NaN	673.823750	1507.537750
BIA-BIA_DEE	NaN	845.261250	2599.551250
BIA-BIA_ECW	NaN	2.881675	30.992395
BIA-BIA_FFM	NaN	14.034413	102.835512
BIA-BIA_FFFI	NaN	12.004050	16.701450
BIA-BIA_FMI	NaN	0.267133	7.963872
BIA-BIA_Fat	NaN	-7.101531	40.171599
BIA-BIA_Frame_num	NaN	-0.500000	3.500000
BIA-BIA_ICW	NaN	13.478725	42.150725
BIA-BIA_LDM	NaN	8.026563	23.463462
BIA-BIA_LST	NaN	13.735050	96.114250
BIA-BIA_SMM	NaN	3.872787	46.350088
BIA-BIA_TBW	NaN	15.323225	73.782825
PAQ_A-PAQ_A_Total	NaN	1.040000	1.040000
PAQ_C-PAQ_C_Total	NaN	-1.355000	5.645000
SDS-SDS_Total_Raw	NaN	24.125000	49.125000
SDS-SDS_Total_T	NaN	35.750000	67.750000
PreInt_EduHx-computerinternet_hoursday	NaN	-3.000000	5.000000

Outliers

Basic_Demos-Age	2
Basic_Demos-Sex	0
CGAS-CGAS_Score	0
Physical-BMI	2
Physical-Height	0

Physical-Weight	0
Physical-Waist_Circumference	0
Physical-Diastolic_BP	1
Physical-HeartRate	0
Physical-Systolic_BP	2
Fitness_Endurance-Max_Stage	0
Fitness_Endurance-Time_Mins	0
Fitness_Endurance-Time_Sec	0
FGC-FGC CU	0
FGC-FGC CU_Zone	0
FGC-FGC GSND	0
FGC-FGC GSND_Zone	0
FGC-FGC GSD	0
FGC-FGC GSD_Zone	0
FGC-FGC PU	1
FGC-FGC PU_Zone	2
FGC-FGC SRL	2
FGC-FGC SRL_Zone	0
FGC-FGC SRR	0
FGC-FGC SRR_Zone	0
FGC-FGC TL	0
FGC-FGC TL_Zone	0
BIA-BIA_Activity_Level_num	1
BIA-BIA_BMC	0
BIA-BIA_BMI	1
BIA-BIA_BMR	0
BIA-BIA_DEE	1
BIA-BIA_ECW	0
BIA-BIA_FFM	0
BIA-BIA_FFFI	0
BIA-BIA_FMI	1
BIA-BIA_Fat	1
BIA-BIA_Frame_num	0
BIA-BIA_ICW	0
BIA-BIA_LDM	0
BIA-BIA_LST	0
BIA-BIA_SMM	0
BIA-BIA_TBW	0
PAQ_A-PAQ_A_Total	0
PAQ_C-PAQ_C_Total	0
SDS-SDS_Total_Raw	0
SDS-SDS_Total_T	0
PreInt_EduHx-computerinternet_hoursday	0

Skewness of Numeric Features in Test Data:

Basic_Demos-Age	0.514853
Basic_Demos-Sex	0.408248

CGAS-CGAS_Score	NaN
Physical-BMI	NaN
Physical-Height	NaN
Physical-Weight	NaN
Physical-Waist_Circumference	NaN
Physical-Diastolic_BP	NaN
Physical-HeartRate	NaN
Physical-Systolic_BP	NaN
Fitness_Endurance-Max_Stage	NaN
Fitness_Endurance-Time_Mins	NaN
Fitness_Endurance-Time_Sec	NaN
FGC-FGC CU	NaN
FGC-FGC CU_Zone	NaN
FGC-FGC GSND	NaN
FGC-FGC GSND_Zone	NaN
FGC-FGC GSD	NaN
FGC-FGC GSD_Zone	NaN
FGC-FGC PU	NaN
FGC-FGC PU_Zone	NaN
FGC-FGC SRL	NaN
FGC-FGC SRL_Zone	NaN
FGC-FGC SRR	NaN
FGC-FGC SRR_Zone	NaN
FGC-FGC TL	NaN
FGC-FGC TL_Zone	NaN
BIA-BIA_Activity_Level_num	NaN
BIA-BIA_BMC	NaN
BIA-BIA_BMI	NaN
BIA-BIA_BMR	NaN
BIA-BIA_DEE	NaN
BIA-BIA_ECW	NaN
BIA-BIA_FFM	NaN
BIA-BIA_FFFI	NaN
BIA-BIA_FMI	NaN
BIA-BIA_Fat	NaN
BIA-BIA_Frame_num	NaN
BIA-BIA_ICW	NaN
BIA-BIA_LDM	NaN
BIA-BIA_LST	NaN
BIA-BIA_SMM	NaN
BIA-BIA_TBW	NaN
PAQ_A-PAQ_A_Total	NaN
PAQ_C-PAQ_C_Total	NaN
SDS-SDS_Total_Raw	NaN
SDS-SDS_Total_T	NaN
PreInt_EduHx-computerinternet_hoursday	NaN

dtype: float64

Kurtosis of Numeric Features in Test Data:

Basic_Demos-Age	0.073754
Basic_Demos-Sex	-1.833333
CGAS-CGAS_Score	NaN
Physical-BMI	NaN
Physical-Height	NaN
Physical-Weight	NaN
Physical-Waist_Circumference	NaN
Physical-Diastolic_BP	NaN
Physical-HeartRate	NaN
Physical-Systolic_BP	NaN
Fitness_Endurance-Max_Stage	NaN
Fitness_Endurance-Time_Mins	NaN
Fitness_Endurance-Time_Sec	NaN
FGC-FGC CU	NaN
FGC-FGC CU_Zone	NaN
FGC-FGC GSND	NaN
FGC-FGC GSND_Zone	NaN
FGC-FGC GSD	NaN
FGC-FGC GSD_Zone	NaN
FGC-FGC PU	NaN
FGC-FGC PU_Zone	NaN
FGC-FGC SRL	NaN
FGC-FGC SRL_Zone	NaN
FGC-FGC SRR	NaN
FGC-FGC SRR_Zone	NaN
FGC-FGC TL	NaN
FGC-FGC TL_Zone	NaN
BIA-BIA_Activity_Level_num	NaN
BIA-BIA_BMC	NaN
BIA-BIA_BMI	NaN
BIA-BIA_BMR	NaN
BIA-BIA_DEE	NaN
BIA-BIA_ECW	NaN
BIA-BIA_FFM	NaN
BIA-BIA_FFCI	NaN
BIA-BIA_FMI	NaN
BIA-BIA_Fat	NaN
BIA-BIA_Frame_num	NaN
BIA-BIA_ICW	NaN
BIA-BIA_LDM	NaN
BIA-BIA_LST	NaN
BIA-BIA_SMM	NaN
BIA-BIA_TBW	NaN
PAQ_A-PAQ_A_Total	NaN
PAQ_C-PAQ_C_Total	NaN
SDS-SDS_Total_Raw	NaN

```
SDS-SDS_Total_T           NaN  
PreInt_EduHx-computerinternet_hoursday      NaN  
dtype: float64
```

```
[59]: ID_arr = list(test_df['id'])  
test_df.head()
```

```
[59]:      id Basic_Demos-Enroll_Season  Basic_Demos-Age  Basic_Demos-Sex  \  
0  00008ff9                  Fall            5              0  
1  000fd460                 Summer           9              0  
2  00105258                 Summer          10              1  
3  00115b9f                 Winter           9              0  
4  0016bb22                 Spring          18              1  
  
CGAS-Season  CGAS-CGAS_Score Physical-Season  Physical-BMI  Physical-Height  \  
0    Winter        51.0       Fall      16.877316      46.0  
1      NaN         NaN       Fall      14.035590      48.0  
2    Fall         71.0       Fall      16.648696      56.5  
3    Fall         71.0     Summer     18.292347      56.0  
4   Summer        NaN        NaN        NaN        NaN  
  
Physical-Weight  Physical-Waist_Circumference  Physical-Diastolic_BP  \  
0        50.8                      NaN                NaN  
1        46.0                      22.0               75.0  
2        75.6                      NaN               65.0  
3        81.6                      NaN               60.0  
4        NaN                      NaN                NaN  
  
Physical-HeartRate  Physical-Systolic_BP Fitness_Endurance-Season  \  
0            NaN                      NaN                NaN  
1          70.0                     122.0              NaN  
2          94.0                     117.0              Fall  
3          97.0                     117.0             Summer  
4            NaN                      NaN                NaN  
  
Fitness_Endurance-Max_Stage  Fitness_Endurance-Time_Mins  \  
0                      NaN                    NaN  
1                      NaN                    NaN  
2                      5.0                   7.0  
3                      6.0                   9.0  
4                      NaN                    NaN  
  
Fitness_Endurance-Time_Sec  FGC-Season  FGC-FGC CU  FGC-FGC CU_Zone  \  
0                      NaN       Fall        0.0        0.0  
1                      NaN       Fall        3.0        0.0  
2                      33.0      Fall       20.0        1.0  
3                      37.0     Summer      18.0        1.0
```

4		NaN	NaN	NaN	NaN	
0	FGC-FGC_GSND	FGC-FGC_GSND_Zone	FGC-FGC_GSD	FGC-FGC_GSD_Zone	FGC-FGC_PU	\
1	NaN	NaN	NaN	NaN	0.0	
2	10.2	1.0	14.7	2.0	5.0	
3	NaN	NaN	NaN	NaN	5.0	
4	NaN	NaN	NaN	NaN	NaN	
0	FGC-FGC_PU_Zone	FGC-FGC_SRL	FGC-FGC_SRL_Zone	FGC-FGC_SRR	\	
1	0.0	7.0	0.0	6.0		
2	0.0	11.0	1.0	11.0		
3	1.0	10.0	1.0	10.0		
4	0.0	7.0	0.0	7.0		
0	NaN	NaN	NaN	NaN	NaN	
0	FGC-FGC_SRR_Zone	FGC-FGC_TL	FGC-FGC_TL_Zone	BIA-Season	\	
1	0.0	6.0	1.0	Fall		
2	1.0	3.0	0.0	Winter		
3	1.0	5.0	0.0	NaN		
4	0.0	7.0	1.0	Summer		
0	NaN	NaN	NaN	NaN	NaN	
0	BIA-BIA_Activity_Level_num	BIA-BIA_BMC	BIA-BIA_BMI	BIA-BIA_BMR	\	
1	2.0	2.66855	16.8792	932.498		
2	2.0	2.57949	14.0371	936.656		
3	NaN	NaN	NaN	NaN		
4	3.0	3.84191	18.2943	1131.430		
0	NaN	NaN	NaN	NaN	NaN	
0	BIA-BIA_DEE	BIA-BIA_ECW	BIA-BIA_FFM	BIA-BIA_FFMI	BIA-BIA_FMI	\
1	1492.00	8.25598	41.5862	13.8177	3.06143	
2	1498.65	6.01993	42.0291	12.8254	1.21172	
3	NaN	NaN	NaN	NaN	NaN	
4	1923.44	15.59250	62.7757	14.0740	4.22033	
0	NaN	NaN	NaN	NaN	NaN	
0	BIA-BIA_Fat	BIA-BIA_Frame_num	BIA-BIA_ICW	BIA-BIA_LDM	BIA-BIA_LST	\
1	9.21377	1.0	24.4349	8.89536	38.9177	
2	3.97085	1.0	21.0352	14.97400	39.4497	
3	NaN	NaN	NaN	NaN	NaN	
4	18.82430	2.0	30.4041	16.77900	58.9338	
0	NaN	NaN	NaN	NaN	NaN	
0	BIA-BIA_SMM	BIA-BIA_TBW	PAQ_A-Season	PAQ_A-PAQ_A_Total	PAQ_C-Season	\
1	19.5413	32.6909	NaN	NaN	NaN	
1	15.4107	27.0552	NaN	NaN	Fall	

2	NaN	NaN	NaN	NaN	Summer
3	26.4798	45.9966	NaN	NaN	Winter
4	NaN	NaN	Summer	1.04	NaN
	PAQ_C-PAQ_C_Total	SDS-Season	SDS-SDS_Total_Raw	SDS-SDS_Total_T	\
0	NaN	NaN	NaN	NaN	NaN
1	2.340	Fall	46.0	64.0	
2	2.170	Fall	38.0	54.0	
3	2.451	Summer	31.0	45.0	
4	NaN	NaN	NaN	NaN	
	PreInt_EduHx-Season	PreInt_EduHx-computerinternet_hoursday			
0	Fall		3.0		
1	Summer		0.0		
2	Summer		2.0		
3	Winter		0.0		
4	NaN		NaN		

[60]: # Step 1: Handle Extreme Outliers in CGAS-CGAS_Score for test_df

```
# Calculate the IQR for CGAS-CGAS_Score
Q1_cgash_test = test_df['CGAS-CGAS_Score'].quantile(0.25)
Q3_cgash_test = test_df['CGAS-CGAS_Score'].quantile(0.75)
IQR_cgash_test = Q3_cgash_test - Q1_cgash_test

# Define bounds for outlier removal
lower_bound_cgash_test = Q1_cgash_test - 1.5 * IQR_cgash_test
upper_bound_cgash_test = Q3_cgash_test + 1.5 * IQR_cgash_test

# Remove extreme outliers in CGAS-CGAS_Score
test_df = test_df[(test_df['CGAS-CGAS_Score'] >= lower_bound_cgash_test) &
                  (test_df['CGAS-CGAS_Score'] <= upper_bound_cgash_test)]

# Display the updated CGAS-CGAS_Score statistics
print("\nUpdated CGAS-CGAS_Score Summary After Outlier Removal:")
print(test_df['CGAS-CGAS_Score'].describe())
```

Updated CGAS-CGAS_Score Summary After Outlier Removal:

count	8.000000
mean	62.500000
std	11.275764
min	50.000000
25%	51.000000
50%	63.000000
75%	71.000000
max	80.000000
Name:	CGAS-CGAS_Score, dtype: float64

```
[61]: # Step 2: Handle Outliers in Physical-BMI Based on Age Group Thresholds for test_df

# Create age group segments for test_df
age_bins_test = [5, 10, 15, 20, 25]
age_labels_test = ['5-10', '11-15', '16-20', '21-25']
test_df['Age_Group'] = pd.cut(test_df['Basic_Demos-Age'], bins=age_bins_test, labels=age_labels_test)

# Define the scientifically accepted BMI thresholds for each age group (same as train_df)
bmi_thresholds_test = {
    '5-10': (14, 24), # Min, Max BMI for age group 5-10
    '11-15': (16, 28),
    '16-20': (18, 30),
    '21-25': (19, 32)
}

# Remove BMI outliers based on the thresholds defined above
for age_group_test, (bmi_min_test, bmi_max_test) in bmi_thresholds_test.items():
    # Define the condition for outlier removal based on BMI thresholds
    condition_test = (
        (test_df['Age_Group'] == age_group_test) &
        ((test_df['Physical-BMI'] < bmi_min_test) | (test_df['Physical-BMI'] > bmi_max_test))
    )
    # Remove outliers for the given age group
    test_df = test_df[~condition_test]

# Display the updated Physical-BMI statistics by age group
print("\nUpdated Physical-BMI Summary After Outlier Removal (Test Data):")
print(test_df.groupby('Age_Group')['Physical-BMI'].describe())
```

Updated Physical-BMI Summary After Outlier Removal (Test Data):

	count	mean	std	min	25%	50%	\
Age_Group							
5-10	2.0	17.470522	1.162237	16.648696	17.059609	17.470522	
11-15	1.0	22.279952		NaN	22.279952	22.279952	
16-20	0.0		NaN		NaN		NaN
21-25	0.0		NaN		NaN		NaN
				75%		max	
Age_Group							
5-10		17.881434	18.292347				
11-15		22.279952	22.279952				
16-20		NaN	NaN				

```

21-25           NaN      NaN
/var/tmp/ipykernel_7796/3117403607.py:28: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a future version of
pandas. Pass observed=False to retain current behavior or observed=True to adopt
the future default and silence this warning.
    print(test_df.groupby('Age_Group')['Physical-BMI'].describe())

```

[62]: # Step 3: Age Group-Based Analysis for test_df

```

# Update numeric_cols to only include columns that are still in test_df
numeric_cols_test = [col for col in numeric_cols if col in test_df.columns]

# Create a summary DataFrame to store age group-based analysis results for
# test_df
age_group_summary_test = test_df.groupby('Age_Group')[numeric_cols_test].
    agg(['mean', 'median', 'std'])

# Display the summary statistics for numeric features based on age group for
# test_df
print("\nAge Group-Based Summary Statistics for Numeric Features (Test Data):")
print(age_group_summary_test)

```

Age Group-Based Summary Statistics for Numeric Features (Test Data):

Age_Group	Basic_Demos-Age			Basic_Demos-Sex			\
	mean	median	std	mean	median	std	
5-10	9.5	9.5	0.707107	0.5	0.5	0.707107	
11-15	12.0	12.0	1.414214	0.5	0.5	0.707107	
16-20	NaN	NaN	NaN	NaN	NaN	NaN	
21-25	NaN	NaN	NaN	NaN	NaN	NaN	
Age_Group	CGAS-CGAS_Score			Physical-BMI			\
	mean	median	std	mean	median	std	
5-10	71.0	71.0	0.000000	17.470522	17.470522	1.162237	
11-15	58.0	58.0	11.313708	22.279952	22.279952	NaN	
16-20	NaN	NaN	NaN	NaN	NaN	NaN	
21-25	NaN	NaN	NaN	NaN	NaN	NaN	
Age_Group	Physical-Height			Physical-Weight			\
	mean	median	std	mean	median	std	
5-10	56.25	56.25	0.353553	78.6	78.6	4.242641	
11-15	59.50	59.50	NaN	112.2	112.2	NaN	
16-20	NaN	NaN	NaN	NaN	NaN	NaN	
21-25	NaN	NaN	NaN	NaN	NaN	NaN	

Physical-Waist_Circumference							Physical-Diastolic_BP			\
	mean	median	std		mean					
Age_Group										
5-10				NaN	NaN	NaN				62.5
11-15				NaN	NaN	NaN				60.0
16-20				NaN	NaN	NaN				NaN
21-25				NaN	NaN	NaN				NaN
Physical-HeartRate							\			
	median	std		mean	median	std				
Age_Group										
5-10	62.5	3.535534		95.5	95.5	2.12132				
11-15	60.0	NaN		73.0	73.0	NaN				
16-20	NaN	NaN		NaN	NaN	NaN				
21-25	NaN	NaN		NaN	NaN	NaN				
Physical-Systolic_BP							Fitness_Endurance-Max_Stage			
	mean	median	std				mean	median		\
Age_Group										
5-10		117.0	117.0	0.0						5.5 5.5
11-15		102.0	102.0	NaN						NaN NaN
16-20		NaN	NaN	NaN						NaN NaN
21-25		NaN	NaN	NaN						NaN NaN
Fitness_Endurance-Time_Mins							\			
	std			mean	median	std				
Age_Group										
5-10	0.707107			8.0	8.0	1.414214				
11-15	NaN			NaN	NaN	NaN				
16-20	NaN			NaN	NaN	NaN				
21-25	NaN			NaN	NaN	NaN				
Fitness_Endurance-Time_Sec							FGC-FGC CU			
	mean	median		std			mean	median		\
Age_Group										
5-10		35.0	35.0	2.828427						19.0 19.0
11-15		NaN	NaN	NaN						12.0 12.0
16-20		NaN	NaN	NaN						NaN NaN
21-25		NaN	NaN	NaN						NaN NaN
FGC-FGC CU_Zone							FGC-FGC GSND			
	std			mean	median	std	mean	median	std	\
Age_Group										
5-10	1.414214			1.0	1.0	0.0				10.2 10.2 NaN
11-15	NaN			0.0	0.0	NaN				16.5 16.5 NaN
16-20	NaN			NaN	NaN	NaN				NaN NaN NaN
21-25	NaN			NaN	NaN	NaN				NaN NaN NaN

	FGC-FGC_GSND_Zone			FGC-FGC_GSD			\
	mean	median	std	mean	median	std	
Age_Group							
5-10	1.0	1.0	NaN	14.7	14.7	NaN	
11-15	2.0	2.0	NaN	17.9	17.9	NaN	
16-20	NaN	NaN	NaN	NaN	NaN	NaN	
21-25	NaN	NaN	NaN	NaN	NaN	NaN	
	FGC-FGC_GSD_Zone			FGC-FGC_PU			\
	mean	median	std	mean	median	std	
Age_Group							
5-10	2.0	2.0	NaN	6.0	6.0	1.414214	
11-15	2.0	2.0	NaN	6.0	6.0	NaN	
16-20	NaN	NaN	NaN	NaN	NaN	NaN	
21-25	NaN	NaN	NaN	NaN	NaN	NaN	
	FGC-FGC_PU_Zone			FGC-FGC_SRL			\
	mean	median	std	mean	median	std	
Age_Group							
5-10	0.5	0.5	0.707107	8.5	8.5	2.12132	
11-15	0.0	0.0	NaN	10.0	10.0	NaN	
16-20	NaN	NaN	NaN	NaN	NaN	NaN	
21-25	NaN	NaN	NaN	NaN	NaN	NaN	
	FGC-FGC_SRL_Zone			FGC-FGC_SRR			\
	mean	median	std	mean	median	std	
Age_Group							
5-10	0.5	0.5	0.707107	8.5	8.5	2.12132	
11-15	1.0	1.0	NaN	11.0	11.0	NaN	
16-20	NaN	NaN	NaN	NaN	NaN	NaN	
21-25	NaN	NaN	NaN	NaN	NaN	NaN	
	FGC-FGC_SRR_Zone			FGC-FGC_TL			\
	mean	median	std	mean	median	std	
Age_Group							
5-10	0.5	0.5	0.707107	6.0	6.0	1.414214	
11-15	1.0	1.0	NaN	8.0	8.0	NaN	
16-20	NaN	NaN	NaN	NaN	NaN	NaN	
21-25	NaN	NaN	NaN	NaN	NaN	NaN	
	FGC-FGC_TL_Zone			BIA-BIA_Activity_Level_num			\
	mean	median	std	mean	median		
Age_Group							
5-10	0.5	0.5	0.707107	3.0	3.0		
11-15	0.0	0.0	NaN	2.0	2.0		
16-20	NaN	NaN	NaN	NaN	NaN		
21-25	NaN	NaN	NaN	NaN	NaN		

	BIA-BIA_BMC			BIA-BIA_BMI			BIA-BIA_BMR			\
	std	mean	median std	mean	median std	mean	median std	mean		
Age_Group										
5-10	NaN	3.84191	3.84191 NaN	18.2943	18.2943 NaN	1131.43				
11-15	NaN	4.33036	4.33036 NaN	30.1865	30.1865 NaN	1330.97				
16-20	NaN	NaN	NaN NaN	NaN	NaN NaN	NaN				
21-25	NaN	NaN	NaN NaN	NaN	NaN NaN	NaN				
	BIA-BIA_DEE			BIA-BIA_ECW			\			
	median std	mean	median std	mean	median std	mean	median std	mean		
Age_Group										
5-10	1131.43 NaN	1923.44	1923.44 NaN	15.5925	15.5925 NaN					
11-15	1330.97 NaN	1996.45	1996.45 NaN	30.2124	30.2124 NaN					
16-20	NaN NaN	NaN	NaN NaN	NaN	NaN NaN					
21-25	NaN NaN	NaN	NaN NaN	NaN	NaN NaN					
	BIA-BIA_FFM			BIA-BIA_FFMI			BIA-BIA_FMI			\
	mean	median std	mean	mean	median std	mean	median std	mean		
Age_Group										
5-10	62.7757	62.7757 NaN		14.0740	14.0740 NaN	4.22033				
11-15	84.0285	84.0285 NaN		16.6877	16.6877 NaN	13.49880				
16-20	NaN	NaN NaN		NaN	NaN NaN	NaN				
21-25	NaN	NaN NaN		NaN	NaN NaN	NaN				
	BIA-BIA_Fat			BIA-BIA_Frame_num			\			
	median std	mean	median std	mean	median std	mean	median std	mean		
Age_Group										
5-10	4.22033 NaN	18.8243	18.8243 NaN			2.0	2.0 NaN			
11-15	13.49880 NaN	67.9715	67.9715 NaN			2.0	2.0 NaN			
16-20	NaN NaN	NaN	NaN NaN			NaN	NaN NaN			
21-25	NaN NaN	NaN	NaN NaN			NaN	NaN NaN			
	BIA-BIA_ICW			BIA-BIA_LDM			BIA-BIA_LST			\
	mean	median std	mean	mean	median std	mean	median std	mean		
Age_Group										
5-10	30.4041	30.4041 NaN		16.779	16.779 NaN	58.9338				
11-15	32.9141	32.9141 NaN		20.902	20.902 NaN	79.6982				
16-20	NaN	NaN NaN		NaN	NaN NaN	NaN				
21-25	NaN	NaN NaN		NaN	NaN NaN	NaN				
	BIA-BIA_SMM			BIA-BIA_TBW			\			
	median std	mean	median std	mean	median std	mean	median std	mean		
Age_Group										
5-10	58.9338 NaN	26.4798	26.4798 NaN	45.9966	45.9966 NaN					
11-15	79.6982 NaN	35.3804	35.3804 NaN	63.1265	63.1265 NaN					
16-20	NaN NaN	NaN	NaN NaN	NaN	NaN NaN					
21-25	NaN NaN	NaN	NaN NaN	NaN	NaN NaN					

	PAQ_A-PAQ_A_Total			PAQ_C-PAQ_C_Total			\
	mean	median	std	mean	median	std	
Age_Group							
5-10	NaN	NaN	NaN	2.3105	2.3105	0.198697	
11-15	NaN	NaN	NaN	2.6050	2.6050	2.128391	
16-20	NaN	NaN	NaN	NaN	NaN	NaN	
21-25	NaN	NaN	NaN	NaN	NaN	NaN	
	SDS-SDS_Total_Raw			SDS-SDS_Total_T			\
	mean	median	std	mean	median	std	
Age_Group							
5-10	34.5	34.5	4.949747	49.5	49.5	6.363961	
11-15	41.0	41.0	1.414214	57.5	57.5	2.121320	
16-20	NaN	NaN	NaN	NaN	NaN	NaN	
21-25	NaN	NaN	NaN	NaN	NaN	NaN	
	PreInt_EduHx-computerinternet_hoursday						
	mean	median	std				
Age_Group							
5-10	1.0	1.0	1.414214				
11-15	0.0	0.0	0.000000				
16-20	NaN	NaN	NaN				
21-25	NaN	NaN	NaN				

/var/tmp/ipykernel_7796/1008554566.py:7: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future default and silence this warning.

```
age_group_summary_test =
test_df.groupby('Age_Group')[numeric_cols_test].agg(['mean', 'median', 'std'])
```

```
[63]: # Step 1: Get categorical columns in test_df
categorical_cols_test = test_df.select_dtypes(include=['object']).columns
```

```
# Step 2: Create a summary dictionary to store analysis results for each categorical feature in test_df
categorical_summary_test = {}
```

```
for col in categorical_cols_test:
    # Get the value counts and missing percentage for test_df
    value_counts_test = test_df[col].value_counts(dropna=False)
    missing_percentage_test = test_df[col].isnull().mean() * 100

    # Store the summary statistics in the dictionary for test_df
    categorical_summary_test[col] = {
        'Value Counts': value_counts_test,
        'Missing Percentage': missing_percentage_test}
```

```

}

# Step 3: Create a DataFrame to display categorical feature summaries for test_df
categorical_summary_test_df = pd.DataFrame({
    'Feature': [col for col in categorical_summary_test.keys()],
    'Value Counts': [str(categorical_summary_test[col]['Value Counts']) for col in categorical_summary_test.keys()],
    'Missing Percentage (%)': [categorical_summary_test[col]['MissingPercentage'] for col in categorical_summary_test.keys()]
})

# Display the summary DataFrame for test_df
print("Categorical Feature Analysis for Test Data:")
print(categorical_summary_test_df)

# Step 4: Check for low-frequency categories (less than 5% frequency) to identify potential consolidation opportunities in test_df
low_freq_categories_test = {}
for col in categorical_cols_test:
    # Identify categories that make up less than 5% of the total count
    low_freq_test = categorical_summary_test[col]['ValueCounts'][categorical_summary_test[col]['Value Counts'] < 0.05 * len(test_df)].index.tolist()
    if low_freq_test:
        low_freq_categories_test[col] = low_freq_test

# Display low-frequency categories if found for test_df
if low_freq_categories_test:
    print("\nLow-Frequency Categories Identified for Potential Consolidation in Test Data:")
    for col, low_freq_test in low_freq_categories_test.items():
        print(f"Feature: {col}")
        print(f"Low-Frequency Categories: {low_freq_test}")
else:
    print("\nNo Low-Frequency Categories Identified for Consolidation in Test Data.")

```

Categorical Feature Analysis for Test Data:

	Feature \
0	id
1	Basic_Demos-Enroll_Season
2	CGAS-Season
3	Physical-Season
4	Fitness_Endurance-Season
5	FGC-Season
6	BIA-Season

```

7          PAQ_A-Season
8          PAQ_C-Season
9          SDS-Season
10         PreInt_EduHx-Season

                                         Value Counts   Missing Percentage (%)
0  id\n00008ff9      1\n00105258    1\n00115b9f     ...
1  Basic_Demos-Enroll_Season\nnFall      2\nnSpring...
2  CGAS-Season\nnWinter      2\nnFall      2\nnSummer ...
3  Physical-Season\nnFall      2\nnSummer      2\nnNaN...
4  Fitness_Endurance-Season\nnNaN      3\nnFall     ...
5  FGC-Season\nnFall      2\nnSummer      2\nnWinter ...
6  BIA-Season\nnNaN      3\nnSummer      2\nnFall     ...
7  PAQ_A-Season\nnNaN      6\nName: count, dtype: int64
8  PAQ_C-Season\nnNaN      2\nnWinter      2\nnSummer...
9  SDS-Season\nnSummer      2\nnNaN      1\nnFall     ...
10 PreInt_EduHx-Season\nnFall      2\nnSpring      2\...

```

No Low-Frequency Categories Identified for Consolidation in Test Data.

```

[64]: import matplotlib.pyplot as plt
import seaborn as sns

# Step 1: Extract numeric columns from test_df
numeric_features_test = test_df.select_dtypes(include=[np.number]).columns

# Step 2: Compute the correlation matrix for the numeric features in test_df
correlation_matrix_test = test_df[numeric_features_test].corr()

# Step 3: Display the correlation matrix to identify relationships between
↳ features in test_df
print("Correlation Matrix for Numeric Features (Test Data):")
print(correlation_matrix_test)

# Step 4: Visualize the correlation matrix using a heatmap to identify
↳ multicollinearity or strong relationships in test_df
plt.figure(figsize=(18, 12))
sns.heatmap(correlation_matrix_test, annot=True, cmap='coolwarm', linewidths=0.
            ↳ 5, fmt='%.2f')
plt.title('Correlation Matrix Heatmap for Numeric Features (Test Data)')
plt.show()

# Step 5: Identify highly correlated pairs in test_df (correlation > 0.8 or <
↳ -0.8)
highly_correlated_pairs_test = []
threshold_test = 0.8

```

```

for i in range(len(correlation_matrix_test.columns)):
    for j in range(i + 1, len(correlation_matrix_test.columns)):
        if abs(correlation_matrix_test.iloc[i, j]) > threshold_test:
            highly_correlated_pairs_test.append(
                (correlation_matrix_test.columns[i], correlation_matrix_test.
                 columns[j], correlation_matrix_test.iloc[i, j])
            )

# Step 6: Display highly correlated pairs if found for test_df
if highly_correlated_pairs_test:
    print("\nHighly Correlated Pairs in Test Data (|correlation| > 0.8):")
    for pair in highly_correlated_pairs_test:
        print(f"Feature 1: {pair[0]}, Feature 2: {pair[1]}, Correlation: {pair[2]:.2f}")
else:
    print("\nNo highly correlated pairs found with |correlation| > 0.8 in Test Data.")

```

	Basic_Demos-Age	Basic_Demos-Sex
Basic_Demos-Age	1.000000e+00	0.168497
Basic_Demos-Sex	1.684968e-01	1.000000
CGAS-CGAS_Score	-2.882110e-01	0.197949
Physical-BMI	7.497721e-01	0.271616
Physical-Height	9.640227e-01	0.184610
Physical-Weight	9.749089e-01	0.256066
Physical-Waist_Circumference	NaN	NaN
Physical-Diastolic_BP	-2.119044e-02	0.420084
Physical-HeartRate	-2.471208e-02	-0.653197
Physical-Systolic_BP	-3.105422e-01	-0.530314
Fitness_Endurance-Max_Stage	-1.000000e+00	-1.000000
Fitness_Endurance-Time_Mins	-1.000000e+00	-1.000000
Fitness_Endurance-Time_Sec	-1.000000e+00	-1.000000
FGC-FGC CU	7.435859e-01	0.095173
FGC-FGC CU_Zone	2.923217e-01	-0.166667
FGC-FGC GSND	1.000000e+00	NaN
FGC-FGC GSND_Zone	1.000000e+00	NaN
FGC-FGC GSD	1.000000e+00	NaN
FGC-FGC GSD_Zone	NaN	NaN
FGC-FGC PU	9.049739e-01	0.298719
FGC-FGC PU_Zone	2.603778e-01	0.408248
FGC-FGC SRL	2.792054e-01	0.993146
FGC-FGC SRL_Zone	3.720458e-01	1.000000
FGC-FGC SRR	5.505464e-01	0.968475
FGC-FGC SRR_Zone	3.720458e-01	1.000000
FGC-FGC TL	3.063858e-01	0.080064
FGC-FGC TL_Zone	-8.238157e-01	-0.666667

BIA-BIA_Activity_Level_num	-1.922963e-16	-0.500000
BIA-BIA_BMC	9.728373e-01	0.726757
BIA-BIA_BMI	9.103617e-01	0.995303
BIA-BIA_BMR	9.999996e-01	0.866466
BIA-BIA_DEE	9.251778e-01	0.611460
BIA-BIA_ECW	9.821499e-01	0.944617
BIA-BIA_FFM	9.999996e-01	0.866456
BIA-BIA_FFFI	9.035463e-01	0.996739
BIA-BIA_FMI	9.122150e-01	0.994857
BIA-BIA_Fat	9.321317e-01	0.988309
BIA-BIA_Frame_num	8.660254e-01	0.500000
BIA-BIA_ICW	9.733643e-01	0.728326
BIA-BIA_LDM	9.840399e-01	0.763230
BIA-BIA_LST	9.999439e-01	0.871274
BIA-BIA_SMM	9.974522e-01	0.899488
BIA-BIA_TBW	9.973791e-01	0.899932
PAQ_A-PAQ_A_Total	Nan	Nan
PAQ_C-PAQ_C_Total	5.649018e-01	0.632346
SDS-SDS_Total_Raw	4.295478e-01	0.241423
SDS-SDS_Total_T	3.838790e-01	0.244600
PreInt_EduHx-computerinternet_hoursday	-4.243216e-01	-0.137361

	CGAS-CGAS_Score	Physical-BMI \
Basic_Demos-Age	-0.288211	0.749772
Basic_Demos-Sex	0.197949	0.271616
CGAS-CGAS_Score	1.000000	-0.522120
Physical-BMI	-0.522120	1.000000
Physical-Height	-0.260793	0.607281
Physical-Weight	-0.419738	0.856963
Physical-Waist_Circumference	Nan	Nan
Physical-Diastolic_BP	0.297044	-0.622059
Physical-HeartRate	0.365655	-0.576780
Physical-Systolic_BP	0.630416	-0.803882
Fitness_Endurance-Max_Stage	Nan	1.000000
Fitness_Endurance-Time_Mins	Nan	1.000000
Fitness_Endurance-Time_Sec	Nan	1.000000
FGC-FGC CU	0.132362	0.176773
FGC-FGC CU_Zone	0.436314	-0.316501
FGC-FGC GSND	-1.000000	1.000000
FGC-FGC GSND_Zone	-1.000000	1.000000
FGC-FGC GSD	-1.000000	1.000000
FGC-FGC GSD_Zone	Nan	Nan
FGC-FGC PU	-0.059984	0.406402
FGC-FGC PU_Zone	0.267187	-0.391428
FGC-FGC SRL	0.313233	0.225014
FGC-FGC SRL_Zone	0.245427	0.271616
FGC-FGC SRR	0.177406	0.473849
FGC-FGC SRR_Zone	0.245427	0.271616

FGC-FGC_TL	-0.225973	0.816606
FGC-FGC_TL_Zone	0.279514	-0.466387
BIA-BIA_Activity_Level_num	0.999109	-0.265082
BIA-BIA_BMC	0.190222	0.876671
BIA-BIA_BMI	-0.451869	0.987489
BIA-BIA_BMR	-0.043088	0.964459
BIA-BIA_DEE	0.340146	0.791473
BIA-BIA_ECW	-0.229386	0.996876
BIA-BIA_FFM	-0.043068	0.964454
BIA-BIA_FFFI	-0.466245	0.984808
BIA-BIA_FMI	-0.447849	0.988189
BIA-BIA_Fat	-0.401140	0.994777
BIA-BIA_Frame_num	0.463002	0.702503
BIA-BIA_ICW	0.187976	0.877769
BIA-BIA_LDM	0.136255	0.901666
BIA-BIA_LST	-0.052789	0.966980
BIA-BIA_SMM	-0.113375	0.980680
BIA-BIA_TBW	-0.114386	0.980878
PAQ_A-PAQ_A_Total	NaN	NaN
PAQ_C-PAQ_C_Total	-0.750481	0.988267
SDS-SDS_Total_Raw	-0.422847	0.374065
SDS-SDS_Total_T	-0.372952	0.318156
PreInt_EduHx-computerinternet_hoursday	-0.366025	-0.566751

	Physical-Height	Physical-Weight	\
Basic_Demos-Age	0.964023	0.974909	
Basic_Demos-Sex	0.184610	0.256066	
CGAS-CGAS_Score	-0.260793	-0.419738	
Physical-BMI	0.607281	0.856963	
Physical-Height	1.000000	0.929547	
Physical-Weight	0.929547	1.000000	
Physical-Waist_Circumference	NaN	NaN	
Physical-Diastolic_BP	0.051154	-0.263705	
Physical-HeartRate	0.280378	-0.118328	
Physical-Systolic_BP	-0.016846	-0.419514	
Fitness_Endurance-Max_Stage	-1.000000	1.000000	
Fitness_Endurance-Time_Mins	-1.000000	1.000000	
Fitness_Endurance-Time_Sec	-1.000000	1.000000	
FGC-FGC CU	0.873480	0.644895	
FGC-FGC CU_Zone	0.507679	0.175349	
FGC-FGC_GSND	1.000000	1.000000	
FGC-FGC_GSND_Zone	1.000000	1.000000	
FGC-FGC_GSD	1.000000	1.000000	
FGC-FGC_GSD_Zone	NaN	NaN	
FGC-FGC PU	0.959337	0.811553	
FGC-FGC PU_Zone	0.331076	0.043463	
FGC-FGC_SRL	0.086848	0.170110	
FGC-FGC_SRL_Zone	0.184610	0.256066	

FGC-FGC_SRR	0.364799	0.463933
FGC-FGC_SRR_Zone	0.184610	0.256066
FGC-FGC_TL	0.167866	0.479004
FGC-FGC_TL_Zone	-0.738442	-0.707660
BIA-BIA_Activity_Level_num	0.267828	0.001881
BIA-BIA_BMC	0.999296	0.973271
BIA-BIA_BMI	0.766273	0.909582
BIA-BIA_BMR	0.963230	0.999996
BIA-BIA_DEE	0.993028	0.925890
BIA-BIA_ECW	0.895890	0.981794
BIA-BIA_FFM	0.963236	0.999996
BIA-BIA_FFMI	0.755775	0.902739
BIA-BIA_FMI	0.769157	0.911443
BIA-BIA_Fat	0.801092	0.931449
BIA-BIA_Frame_num	0.968301	0.866964
BIA-BIA_ICW	0.999207	0.973794
BIA-BIA_LDM	0.995749	0.984373
BIA-BIA_LST	0.960575	0.999922
BIA-BIA_SMM	0.941906	0.997316
BIA-BIA_TBW	0.941563	0.997241
PAQ_A-PAQ_A_Total	NaN	NaN
PAQ_C-PAQ_C_Total	0.964600	0.999819
SDS-SDS_Total_Raw	0.088035	0.263425
SDS-SDS_Total_T	0.030251	0.198970
PreInt_EduHx-computerinternet_hoursday	-0.280890	-0.432538

	Physical-Waist_Circumference \	
Basic_Demos-Age		NaN
Basic_Demos-Sex		NaN
CGAS-CGAS_Score		NaN
Physical-BMI		NaN
Physical-Height		NaN
Physical-Weight		NaN
Physical-Waist_Circumference		NaN
Physical-Diastolic_BP		NaN
Physical-HeartRate		NaN
Physical-Systolic_BP		NaN
Fitness_Endurance-Max_Stage		NaN
Fitness_Endurance-Time_Mins		NaN
Fitness_Endurance-Time_Sec		NaN
FGC-FGC CU		NaN
FGC-FGC CU_Zone		NaN
FGC-FGC GSND		NaN
FGC-FGC GSND_Zone		NaN
FGC-FGC GSD		NaN
FGC-FGC GSD_Zone		NaN
FGC-FGC PU		NaN
FGC-FGC PU_Zone		NaN

FGC-FGC_SRL	NaN
FGC-FGC_SRL_Zone	NaN
FGC-FGC_SRR	NaN
FGC-FGC_SRR_Zone	NaN
FGC-FGC_TL	NaN
FGC-FGC_TL_Zone	NaN
BIA-BIA_Activity_Level_num	NaN
BIA-BIA_BMC	NaN
BIA-BIA_BMI	NaN
BIA-BIA_BMR	NaN
BIA-BIA_DEE	NaN
BIA-BIA_ECW	NaN
BIA-BIA_FFM	NaN
BIA-BIA_FFMI	NaN
BIA-BIA_FMI	NaN
BIA-BIA_Fat	NaN
BIA-BIA_Frame_num	NaN
BIA-BIA_ICW	NaN
BIA-BIA_LDM	NaN
BIA-BIA_LST	NaN
BIA-BIA_SMM	NaN
BIA-BIA_TBW	NaN
PAQ_A-PAQ_A_Total	NaN
PAQ_C-PAQ_C_Total	NaN
SDS-SDS_Total_Raw	NaN
SDS-SDS_Total_T	NaN
PreInt_EduHx-computerinternet_hoursday	NaN

	Physical-Diastolic_BP \
Basic_Demos-Age	-0.021190
Basic_Demos-Sex	0.420084
CGAS-CGAS_Score	0.297044
Physical-BMI	-0.622059
Physical-Height	0.051154
Physical-Weight	-0.263705
Physical-Waist_Circumference	NaN
Physical-Diastolic_BP	1.000000
Physical-HeartRate	0.411597
Physical-Systolic_BP	0.513355
Fitness_Endurance-Max_Stage	-1.000000
Fitness_Endurance-Time_Mins	-1.000000
Fitness_Endurance-Time_Sec	-1.000000
FGC-FGC CU	0.388967
FGC-FGC CU_Zone	0.485071
FGC-FGC GSND	-1.000000
FGC-FGC GSND_Zone	-1.000000
FGC-FGC GSD	-1.000000
FGC-FGC GSD_Zone	NaN

FGC-FGC_PU	0.360302
FGC-FGC_PU_Zone	0.980196
FGC-FGC_SRL	0.371768
FGC-FGC_SRL_Zone	0.420084
FGC-FGC_SRR	0.242536
FGC-FGC_SRR_Zone	0.420084
FGC-FGC_TL	-0.945905
FGC-FGC_TL_Zone	-0.485071
BIA-BIA_Activity_Level_num	NaN
BIA-BIA_BMC	NaN
BIA-BIA_BMI	NaN
BIA-BIA_BMR	NaN
BIA-BIA_DEE	NaN
BIA-BIA_ECW	NaN
BIA-BIA_FFM	NaN
BIA-BIA_FFMI	NaN
BIA-BIA_FMI	NaN
BIA-BIA_Fat	NaN
BIA-BIA_Frame_num	NaN
BIA-BIA_ICW	NaN
BIA-BIA_LDM	NaN
BIA-BIA_LST	NaN
BIA-BIA_SMM	NaN
BIA-BIA_TBW	NaN
PAQ_A-PAQ_A_Total	NaN
PAQ_C-PAQ_C_Total	-0.611549
SDS-SDS_Total_Raw	0.289241
SDS-SDS_Total_T	0.318874
PreInt_EduHx-computerinternet_hoursday	0.980196

	Physical-HeartRate \
Basic_Demos-Age	-0.024712
Basic_Demos-Sex	-0.653197
CGAS-CGAS_Score	0.365655
Physical-BMI	-0.576780
Physical-Height	0.280378
Physical-Weight	-0.118328
Physical-Waist_Circumference	NaN
Physical-Diastolic_BP	0.411597
Physical-HeartRate	1.000000
Physical-Systolic_BP	0.948835
Fitness_Endurance-Max_Stage	1.000000
Fitness_Endurance-Time_Mins	1.000000
Fitness_Endurance-Time_Sec	1.000000
FGC-FGC CU	0.762063
FGC-FGC CU_Zone	0.989949
FGC-FGC GSND	-1.000000
FGC-FGC GSND_Zone	-1.000000

FGC-FGC_GSD	-1.000000
FGC-FGC_GSD_Zone	NaN
FGC-FGC_PU	0.446442
FGC-FGC_PU_Zone	0.489898
FGC-FGC_SRL	-0.688583
FGC-FGC_SRL_Zone	-0.653197
FGC-FGC_SRR	-0.754247
FGC-FGC_SRR_Zone	-0.653197
FGC-FGC_TL	-0.648886
FGC-FGC_TL_Zone	0.141421
BIA-BIA_Activity_Level_num	1.000000
BIA-BIA_BMC	-1.000000
BIA-BIA_BMI	-1.000000
BIA-BIA_BMR	-1.000000
BIA-BIA_DEE	-1.000000
BIA-BIA_ECW	-1.000000
BIA-BIA_FFM	-1.000000
BIA-BIA_FFMI	-1.000000
BIA-BIA_FMI	-1.000000
BIA-BIA_Fat	-1.000000
BIA-BIA_Frame_num	NaN
BIA-BIA_ICW	-1.000000
BIA-BIA_LDM	-1.000000
BIA-BIA_LST	-1.000000
BIA-BIA_SMM	-1.000000
BIA-BIA_TBW	-1.000000
PAQ_A-PAQ_A_Total	NaN
PAQ_C-PAQ_C_Total	-0.969066
SDS-SDS_Total_Raw	-0.695701
SDS-SDS_Total_T	-0.693026
PreInt_EduHx-computerinternet_hoursday	0.489898

	Physical-Systolic_BP \
Basic_Demos-Age	-0.310542
Basic_Demos-Sex	-0.530314
CGAS-CGAS_Score	0.630416
Physical-BMI	-0.803882
Physical-Height	-0.016846
Physical-Weight	-0.419514
Physical-Waist_Circumference	NaN
Physical-Diastolic_BP	0.513355
Physical-HeartRate	0.948835
Physical-Systolic_BP	1.000000
Fitness_Endurance-Max_Stage	NaN
Fitness_Endurance-Time_Mins	NaN
Fitness_Endurance-Time_Sec	NaN
FGC-FGC CU	0.550810
FGC-FGC CU_Zone	0.918532

FGC-FGC_GSND	-1.000000
FGC-FGC_GSND_Zone	-1.000000
FGC-FGC_GSD	-1.000000
FGC-FGC_GSD_Zone	NaN
FGC-FGC_PU	0.200231
FGC-FGC_PU_Zone	0.530314
FGC-FGC_SRL	-0.529335
FGC-FGC_SRL_Zone	-0.530314
FGC-FGC_SRR	-0.705539
FGC-FGC_SRR_Zone	-0.530314
FGC-FGC_TL	-0.760444
FGC-FGC_TL_Zone	0.279553
BIA-BIA_Activity_Level_num	1.000000
BIA-BIA_BMC	-1.000000
BIA-BIA_BMI	-1.000000
BIA-BIA_BMR	-1.000000
BIA-BIA_DEE	-1.000000
BIA-BIA_ECW	-1.000000
BIA-BIA_FFM	-1.000000
BIA-BIA_FFMI	-1.000000
BIA-BIA_FMI	-1.000000
BIA-BIA_Fat	-1.000000
BIA-BIA_Frame_num	NaN
BIA-BIA_ICW	-1.000000
BIA-BIA_LDM	-1.000000
BIA-BIA_LST	-1.000000
BIA-BIA_SMM	-1.000000
BIA-BIA_TBW	-1.000000
PAQ_A-PAQ_A_Total	NaN
PAQ_C-PAQ_C_Total	-0.990979
SDS-SDS_Total_Raw	-0.672726
SDS-SDS_Total_T	-0.649167
PreInt_EduHx-computerinternet_hoursday	0.530314

	Fitness_Endurance-Max_Stage \
Basic_Demos-Age	-1.0
Basic_Demos-Sex	-1.0
CGAS-CGAS_Score	NaN
Physical-BMI	1.0
Physical-Height	-1.0
Physical-Weight	1.0
Physical-Waist_Circumference	NaN
Physical-Diastolic_BP	-1.0
Physical-HeartRate	1.0
Physical-Systolic_BP	NaN
Fitness_Endurance-Max_Stage	1.0
Fitness_Endurance-Time_Mins	1.0
Fitness_Endurance-Time_Sec	1.0

FGC-FGC CU	-1.0
FGC-FGC CU_Zone	NaN
FGC-FGC GSND	NaN
FGC-FGC GSND_Zone	NaN
FGC-FGC GSD	NaN
FGC-FGC GSD_Zone	NaN
FGC-FGC PU	-1.0
FGC-FGC PU_Zone	-1.0
FGC-FGC SRL	-1.0
FGC-FGC SRL_Zone	-1.0
FGC-FGC SRR	-1.0
FGC-FGC SRR_Zone	-1.0
FGC-FGC TL	1.0
FGC-FGC TL_Zone	1.0
BIA-BIA_Activity_Level_num	NaN
BIA-BIA_BMC	NaN
BIA-BIA_BMI	NaN
BIA-BIA_BMR	NaN
BIA-BIA_DEE	NaN
BIA-BIA_ECW	NaN
BIA-BIA_FFM	NaN
BIA-BIA_FFMI	NaN
BIA-BIA_FMI	NaN
BIA-BIA_Fat	NaN
BIA-BIA_Frame_num	NaN
BIA-BIA_ICW	NaN
BIA-BIA_LDM	NaN
BIA-BIA_LST	NaN
BIA-BIA_SMM	NaN
BIA-BIA_TBW	NaN
PAQ_A-PAQ_A_Total	NaN
PAQ_C-PAQ_C_Total	1.0
SDS-SDS_Total_Raw	-1.0
SDS-SDS_Total_T	-1.0
PreInt_EduHx-computerinternet_hoursday	-1.0

	Fitness_Endurance-Time_Mins \
Basic_Demos-Age	-1.0
Basic_Demos-Sex	-1.0
CGAS-CGAS_Score	NaN
Physical-BMI	1.0
Physical-Height	-1.0
Physical-Weight	1.0
Physical-Waist_Circumference	NaN
Physical-Diastolic_BP	-1.0
Physical-HeartRate	1.0
Physical-Systolic_BP	NaN
Fitness_Endurance-Max_Stage	1.0

Fitness_Endurance-Time_Mins	1.0
Fitness_Endurance-Time_Sec	1.0
FGC-FGC CU	-1.0
FGC-FGC CU_Zone	NaN
FGC-FGC GSND	NaN
FGC-FGC GSND_Zone	NaN
FGC-FGC GSD	NaN
FGC-FGC GSD_Zone	NaN
FGC-FGC PU	-1.0
FGC-FGC PU_Zone	-1.0
FGC-FGC SRL	-1.0
FGC-FGC SRL_Zone	-1.0
FGC-FGC SRR	-1.0
FGC-FGC SRR_Zone	-1.0
FGC-FGC TL	1.0
FGC-FGC TL_Zone	1.0
BIA-BIA_Activity_Level_num	NaN
BIA-BIA_BMC	NaN
BIA-BIA_BMI	NaN
BIA-BIA_BMR	NaN
BIA-BIA_DEE	NaN
BIA-BIA_ECW	NaN
BIA-BIA_FFM	NaN
BIA-BIA_FFMI	NaN
BIA-BIA_FMI	NaN
BIA-BIA_Fat	NaN
BIA-BIA_Frame_num	NaN
BIA-BIA_ICW	NaN
BIA-BIA_LDM	NaN
BIA-BIA_LST	NaN
BIA-BIA_SMM	NaN
BIA-BIA_TBW	NaN
PAQ_A-PAQ_A_Total	NaN
PAQ_C-PAQ_C_Total	1.0
SDS-SDS_Total_Raw	-1.0
SDS-SDS_Total_T	-1.0
PreInt_EduHx-computerinternet_hoursday	-1.0

	Fitness_Endurance-Time_Sec \
Basic_Demos-Age	-1.0
Basic_Demos-Sex	-1.0
CGAS-CGAS_Score	NaN
Physical-BMI	1.0
Physical-Height	-1.0
Physical-Weight	1.0
Physical-Waist_Circumference	NaN
Physical-Diastolic_BP	-1.0
Physical-HeartRate	1.0

Physical-Systolic_BP		NaN
Fitness_Endurance-Max_Stage		1.0
Fitness_Endurance-Time_Mins		1.0
Fitness_Endurance-Time_Sec		1.0
FGC-FGC CU		-1.0
FGC-FGC CU_Zone		NaN
FGC-FGC GSND		NaN
FGC-FGC GSND_Zone		NaN
FGC-FGC GSD		NaN
FGC-FGC GSD_Zone		NaN
FGC-FGC PU		-1.0
FGC-FGC PU_Zone		-1.0
FGC-FGC SRL		-1.0
FGC-FGC SRL_Zone		-1.0
FGC-FGC SRR		-1.0
FGC-FGC SRR_Zone		-1.0
FGC-FGC TL		1.0
FGC-FGC TL_Zone		1.0
BIA-BIA_Activity_Level_num		NaN
BIA-BIA_BMC		NaN
BIA-BIA_BMI		NaN
BIA-BIA_BMR		NaN
BIA-BIA_DEE		NaN
BIA-BIA_ECW		NaN
BIA-BIA_FFM		NaN
BIA-BIA_FFMI		NaN
BIA-BIA_FMI		NaN
BIA-BIA_Fat		NaN
BIA-BIA_Frame_num		NaN
BIA-BIA_ICW		NaN
BIA-BIA_LDM		NaN
BIA-BIA_LST		NaN
BIA-BIA_SMM		NaN
BIA-BIA_TBW		NaN
PAQ_A-PAQ_A_Total		NaN
PAQ_C-PAQ_C_Total		1.0
SDS-SDS_Total_Raw		-1.0
SDS-SDS_Total_T		-1.0
PreInt_EduHx-computerinternet_hoursday		-1.0

	FGC-FGC CU	FGC-FGC CU_Zone	\
Basic_Demos-Age	0.743586	2.923217e-01	
Basic_Demos-Sex	0.095173	-1.666667e-01	
CGAS-CGAS_Score	0.132362	4.363141e-01	
Physical-BMI	0.176773	-3.165009e-01	
Physical-Height	0.873480	5.076788e-01	
Physical-Weight	0.644895	1.753494e-01	
Physical-Waist_Circumference		NaN	NaN

Physical-Diastolic_BP	0.388967	4.850713e-01
Physical-HeartRate	0.762063	9.899495e-01
Physical-Systolic_BP	0.550810	9.185315e-01
Fitness_Endurance-Max_Stage	-1.000000	NaN
Fitness_Endurance-Time_Mins	-1.000000	NaN
Fitness_Endurance-Time_Sec	-1.000000	NaN
FGC-FGC_CU	1.000000	8.565604e-01
FGC-FGC_CU_Zone	0.856560	1.000000e+00
FGC-FGC_GSND	-1.000000	-1.000000e+00
FGC-FGC_GSND_Zone	-1.000000	-1.000000e+00
FGC-FGC_GSD	-1.000000	-1.000000e+00
FGC-FGC_GSD_Zone	NaN	NaN
FGC-FGC_PU	0.945947	6.517505e-01
FGC-FGC_PU_Zone	0.582816	6.123724e-01
FGC-FGC_SRL	0.014924	-2.090833e-01
FGC-FGC_SRL_Zone	0.095173	-1.666667e-01
FGC-FGC_SRR	0.216406	-1.263228e-01
FGC-FGC_SRR_Zone	0.095173	-1.666667e-01
FGC-FGC_TL	-0.182879	-4.803845e-01
FGC-FGC_TL_Zone	-0.571040	-1.666667e-01
BIA-BIA_Activity_Level_num	0.755929	1.000000e+00
BIA-BIA_BMC	0.811861	2.314897e-01
BIA-BIA_BMI	0.283158	-4.138134e-01
BIA-BIA_BMR	0.653987	-8.809372e-04
BIA-BIA_DEE	0.892572	3.795341e-01
BIA-BIA_ECW	0.500778	-1.880999e-01
BIA-BIA_FFM	0.654003	-8.610810e-04
BIA-BIA_FFMI	0.267602	-4.284905e-01
BIA-BIA_FMI	0.287472	-4.097119e-01
BIA-BIA_Fat	0.336487	-3.621194e-01
BIA-BIA_Frame_num	0.944911	5.000000e-01
BIA-BIA_ICW	0.810524	2.292639e-01
BIA-BIA_LDM	0.778721	1.779477e-01
BIA-BIA_LST	0.646609	-1.059347e-02
BIA-BIA_SMM	0.599059	-7.133819e-02
BIA-BIA_TBW	0.598244	-7.235330e-02
PAQ_A-PAQ_A_Total	NaN	NaN
PAQ_C-PAQ_C_Total	-0.994158	-9.909795e-01
SDS-SDS_Total_Raw	-0.258199	-5.962848e-01
SDS-SDS_Total_T	-0.291361	-5.976143e-01
PreInt_EduHx-computerinternet_hoursday	-0.184302	-7.166459e-17

	FGC-FGC_GSND	FGC-FGC_GSND_Zone	\
Basic_Demos-Age	1.0	1.0	
Basic_Demos-Sex	NaN	NaN	
CGAS-CGAS_Score	-1.0	-1.0	
Physical-BMI	1.0	1.0	
Physical-Height	1.0	1.0	

Physical-Weight	1.0	1.0
Physical-Waist_Circumference	NaN	NaN
Physical-Diastolic_BP	-1.0	-1.0
Physical-HeartRate	-1.0	-1.0
Physical-Systolic_BP	-1.0	-1.0
Fitness_Endurance-Max_Stage	NaN	NaN
Fitness_Endurance-Time_Mins	NaN	NaN
Fitness_Endurance-Time_Sec	NaN	NaN
FGC-FGC CU	-1.0	-1.0
FGC-FGC CU_Zone	-1.0	-1.0
FGC-FGC GSND	1.0	1.0
FGC-FGC GSND_Zone	1.0	1.0
FGC-FGC GSD	1.0	1.0
FGC-FGC GSD_Zone	NaN	NaN
FGC-FGC PU	-1.0	-1.0
FGC-FGC PU_Zone	-1.0	-1.0
FGC-FGC SRL	NaN	NaN
FGC-FGC SRL_Zone	NaN	NaN
FGC-FGC SRR	1.0	1.0
FGC-FGC SRR_Zone	NaN	NaN
FGC-FGC TL	1.0	1.0
FGC-FGC TL_Zone	NaN	NaN
BIA-BIA_Activity_Level_num	NaN	NaN
BIA-BIA_BMC	NaN	NaN
BIA-BIA_BMI	NaN	NaN
BIA-BIA_BMR	NaN	NaN
BIA-BIA_DEE	NaN	NaN
BIA-BIA_ECW	NaN	NaN
BIA-BIA_FFM	NaN	NaN
BIA-BIA_FFFI	NaN	NaN
BIA-BIA_FMI	NaN	NaN
BIA-BIA_Fat	NaN	NaN
BIA-BIA_Frame_num	NaN	NaN
BIA-BIA_ICW	NaN	NaN
BIA-BIA_LDM	NaN	NaN
BIA-BIA_LST	NaN	NaN
BIA-BIA_SMM	NaN	NaN
BIA-BIA_TBW	NaN	NaN
PAQ_A-PAQ_A_Total	NaN	NaN
PAQ_C-PAQ_C_Total	1.0	1.0
SDS-SDS_Total_Raw	1.0	1.0
SDS-SDS_Total_T	1.0	1.0
PreInt_EduHx-computerinternet_hoursday	-1.0	-1.0

FGC-FGC_GSD	FGC-FGC_GSD_Zone	\
Basic_Demos-Age	1.0	NaN
Basic_Demos-Sex	NaN	NaN
CGAS-CGAS_Score	-1.0	NaN

Physical-BMI	1.0	NaN
Physical-Height	1.0	NaN
Physical-Weight	1.0	NaN
Physical-Waist_Circumference	NaN	NaN
Physical-Diastolic_BP	-1.0	NaN
Physical-HeartRate	-1.0	NaN
Physical-Systolic_BP	-1.0	NaN
Fitness_Endurance-Max_Stage	NaN	NaN
Fitness_Endurance-Time_Mins	NaN	NaN
Fitness_Endurance-Time_Sec	NaN	NaN
FGC-FGC CU	-1.0	NaN
FGC-FGC CU_Zone	-1.0	NaN
FGC-FGC GSND	1.0	NaN
FGC-FGC GSND_Zone	1.0	NaN
FGC-FGC GSD	1.0	NaN
FGC-FGC GSD_Zone	NaN	NaN
FGC-FGC PU	-1.0	NaN
FGC-FGC PU_Zone	-1.0	NaN
FGC-FGC SRL	NaN	NaN
FGC-FGC SRL_Zone	NaN	NaN
FGC-FGC SRR	1.0	NaN
FGC-FGC SRR_Zone	NaN	NaN
FGC-FGC TL	1.0	NaN
FGC-FGC TL_Zone	NaN	NaN
BIA-BIA_Activity_Level_num	NaN	NaN
BIA-BIA_BMC	NaN	NaN
BIA-BIA_BMI	NaN	NaN
BIA-BIA_BMR	NaN	NaN
BIA-BIA_DEE	NaN	NaN
BIA-BIA_ECW	NaN	NaN
BIA-BIA_FFM	NaN	NaN
BIA-BIA_FFMI	NaN	NaN
BIA-BIA_FMI	NaN	NaN
BIA-BIA_Fat	NaN	NaN
BIA-BIA_Frame_num	NaN	NaN
BIA-BIA_ICW	NaN	NaN
BIA-BIA_LDM	NaN	NaN
BIA-BIA_LST	NaN	NaN
BIA-BIA_SMM	NaN	NaN
BIA-BIA_TBW	NaN	NaN
PAQ_A-PAQ_A_Total	NaN	NaN
PAQ_C-PAQ_C_Total	1.0	NaN
SDS-SDS_Total_Raw	1.0	NaN
SDS-SDS_Total_T	1.0	NaN
PreInt_EduHx-computerinternet_hoursday	-1.0	NaN

FGC-FGC PU FGC-FGC PU_Zone \\\nBasic_Demos-Age 0.904974 0.260378

Basic_Demos-Sex	0.298719	0.408248
CGAS-CGAS_Score	-0.059984	0.267187
Physical-BMI	0.406402	-0.391428
Physical-Height	0.959337	0.331076
Physical-Weight	0.811553	0.043463
Physical-Waist_Circumference	NaN	NaN
Physical-Diastolic_BP	0.360302	0.980196
Physical-HeartRate	0.446442	0.489898
Physical-Systolic_BP	0.200231	0.530314
Fitness_Endurance-Max_Stage	-1.000000	-1.000000
Fitness_Endurance-Time_Mins	-1.000000	-1.000000
Fitness_Endurance-Time_Sec	-1.000000	-1.000000
FGC-FGC CU	0.945947	0.582816
FGC-FGC CU_Zone	0.651751	0.612372
FGC-FGC GSND	-1.000000	-1.000000
FGC-FGC GSND_Zone	-1.000000	-1.000000
FGC-FGC GSD	-1.000000	-1.000000
FGC-FGC GSD_Zone	NaN	NaN
FGC-FGC PU	1.000000	0.565412
FGC-FGC PU_Zone	0.565412	1.000000
FGC-FGC SRL	0.204405	0.352101
FGC-FGC SRL_Zone	0.298719	0.408248
FGC-FGC SRR	0.432237	0.309426
FGC-FGC SRR_Zone	0.298719	0.408248
FGC-FGC TL	-0.052182	-0.784465
FGC-FGC TL_Zone	-0.787532	-0.612372
BIA-BIA_Activity_Level_num	0.359211	NaN
BIA-BIA_BMC	0.991060	NaN
BIA-BIA_BMI	0.700955	NaN
BIA-BIA_BMR	0.932940	NaN
BIA-BIA_DEE	0.999761	NaN
BIA-BIA_ECW	0.849030	NaN
BIA-BIA_FFM	0.932947	NaN
BIA-BIA_FFFI	0.689322	NaN
BIA-BIA_FMI	0.704158	NaN
BIA-BIA_Fat	0.739841	NaN
BIA-BIA_Frame_num	0.987829	NaN
BIA-BIA_ICW	0.990753	NaN
BIA-BIA_LDM	0.982282	NaN
BIA-BIA_LST	0.929399	NaN
BIA-BIA_SMM	0.905253	NaN
BIA-BIA_TBW	0.904820	NaN
PAQ_A-PAQ_A_Total	NaN	NaN
PAQ_C-PAQ_C_Total	-0.134014	-0.611549
SDS-SDS_Total_Raw	0.110727	0.258199
SDS-SDS_Total_T	0.066585	0.276026
PreInt_EduHx-computerinternet_hoursday	-0.210352	0.395285

	FGC-FGC_SRL	FGC-FGC_SRL_Zone	\
Basic_Demos-Age	0.279205	0.372046	
Basic_Demos-Sex	0.993146	1.000000	
CGAS-CGAS_Score	0.313233	0.245427	
Physical-BMI	0.225014	0.271616	
Physical-Height	0.086848	0.184610	
Physical-Weight	0.170110	0.256066	
Physical-Waist_Circumference	NaN	NaN	
Physical-Diastolic_BP	0.371768	0.420084	
Physical-HeartRate	-0.688583	-0.653197	
Physical-Systolic_BP	-0.529335	-0.530314	
Fitness_Endurance-Max_Stage	-1.000000	-1.000000	
Fitness_Endurance-Time_Mins	-1.000000	-1.000000	
Fitness_Endurance-Time_Sec	-1.000000	-1.000000	
FGC-FGC CU	0.014924	0.095173	
FGC-FGC CU_Zone	-0.209083	-0.166667	
FGC-FGC GSND	NaN	NaN	
FGC-FGC GSND_Zone	NaN	NaN	
FGC-FGC GSD	NaN	NaN	
FGC-FGC GSD_Zone	NaN	NaN	
FGC-FGC PU	0.204405	0.298719	
FGC-FGC PU_Zone	0.352101	0.408248	
FGC-FGC SRL	1.000000	0.993146	
FGC-FGC SRL_Zone	0.993146	1.000000	
FGC-FGC SRR	0.950832	0.968475	
FGC-FGC SRR_Zone	0.993146	1.000000	
FGC-FGC TL	0.100440	0.080064	
FGC-FGC TL_Zone	-0.574979	-0.666667	
BIA-BIA_Activity_Level_num	-0.500000	-0.500000	
BIA-BIA_BMC	0.726757	0.726757	
BIA-BIA_BMI	0.995303	0.995303	
BIA-BIA_BMR	0.866466	0.866466	
BIA-BIA_DEE	0.611460	0.611460	
BIA-BIA_ECW	0.944617	0.944617	
BIA-BIA_FFM	0.866456	0.866456	
BIA-BIA_FFFI	0.996739	0.996739	
BIA-BIA_FMI	0.994857	0.994857	
BIA-BIA_Fat	0.988309	0.988309	
BIA-BIA_Frame_num	0.500000	0.500000	
BIA-BIA_ICW	0.728326	0.728326	
BIA-BIA_LDM	0.763230	0.763230	
BIA-BIA_LST	0.871274	0.871274	
BIA-BIA_SMM	0.899488	0.899488	
BIA-BIA_TBW	0.899932	0.899932	
PAQ_A-PAQ_A_Total	NaN	NaN	
PAQ_C-PAQ_C_Total	0.379430	0.379430	
SDS-SDS_Total_Raw	0.900567	0.946729	
SDS-SDS_Total_T	0.926823	0.966092	

PreInt_EduHx-computerinternet_hoursday	-0.354277	-0.322749
	FGC-FGC_SRR	FGC-FGC_SRR_Zone \
Basic_Demos-Age	0.550546	0.372046
Basic_Demos-Sex	0.968475	1.000000
CGAS-CGAS_Score	0.177406	0.245427
Physical-BMI	0.473849	0.271616
Physical-Height	0.364799	0.184610
Physical-Weight	0.463933	0.256066
Physical-Waist_Circumference	NaN	NaN
Physical-Diastolic_BP	0.242536	0.420084
Physical-HeartRate	-0.754247	-0.653197
Physical-Systolic_BP	-0.705539	-0.530314
Fitness_Endurance-Max_Stage	-1.000000	-1.000000
Fitness_Endurance-Time_Mins	-1.000000	-1.000000
Fitness_Endurance-Time_Sec	-1.000000	-1.000000
FGC-FGC CU	0.216406	0.095173
FGC-FGC CU_Zone	-0.126323	-0.166667
FGC-FGC GSND	1.000000	NaN
FGC-FGC GSND_Zone	1.000000	NaN
FGC-FGC GSD	1.000000	NaN
FGC-FGC GSD_Zone	NaN	NaN
FGC-FGC PU	0.432237	0.298719
FGC-FGC PU_Zone	0.309426	0.408248
FGC-FGC SRL	0.950832	0.993146
FGC-FGC SRL_Zone	0.968475	1.000000
FGC-FGC SRR	1.000000	0.968475
FGC-FGC SRR_Zone	0.968475	1.000000
FGC-FGC TL	0.262962	0.080064
FGC-FGC TL_Zone	-0.715829	-0.666667
BIA-BIA_Activity_Level_num	-0.327327	-0.500000
BIA-BIA_BMC	0.843472	0.726757
BIA-BIA_BMI	0.995663	0.995303
BIA-BIA_BMR	0.945199	0.866466
BIA-BIA_DEE	0.749979	0.611460
BIA-BIA_ECW	0.989615	0.944617
BIA-BIA_FFM	0.945193	0.866456
BIA-BIA_FFFI	0.994027	0.996739
BIA-BIA_FMI	0.996072	0.994857
BIA-BIA_Fat	0.999313	0.988309
BIA-BIA_Frame_num	0.654654	0.500000
BIA-BIA_ICW	0.844699	0.728326
BIA-BIA_LDM	0.871583	0.763230
BIA-BIA_LST	0.948326	0.871274
BIA-BIA_SMM	0.965855	0.899488
BIA-BIA_TBW	0.966118	0.899932
PAQ_A-PAQ_A_Total	NaN	NaN
PAQ_C-PAQ_C_Total	0.590553	0.379430

SDS-SDS_Total_Raw	0.993808	0.946729
SDS-SDS_Total_T	0.996024	0.966092
PreInt_EduHx-computerinternet_hoursday	-0.489246	-0.322749
	FGC-FGC_TL	FGC-FGC_TL_Zone \
Basic_Demos-Age	3.063858e-01	-8.238157e-01
Basic_Demos-Sex	8.006408e-02	-6.666667e-01
CGAS-CGAS_Score	-2.259734e-01	2.795137e-01
Physical-BMI	8.166062e-01	-4.663872e-01
Physical-Height	1.678662e-01	-7.384419e-01
Physical-Weight	4.790038e-01	-7.076602e-01
Physical-Waist_Circumference		NaN
Physical-Diastolic_BP	-9.459053e-01	-4.850713e-01
Physical-HeartRate	-6.488857e-01	1.414214e-01
Physical-Systolic_BP	-7.604445e-01	2.795531e-01
Fitness_Endurance-Max_Stage	1.000000e+00	1.000000e+00
Fitness_Endurance-Time_Mins	1.000000e+00	1.000000e+00
Fitness_Endurance-Time_Sec	1.000000e+00	1.000000e+00
FGC-FGC CU	-1.828792e-01	-5.710402e-01
FGC-FGC CU_Zone	-4.803845e-01	-1.666667e-01
FGC-FGC GSND	1.000000e+00	NaN
FGC-FGC GSND_Zone	1.000000e+00	NaN
FGC-FGC GSD	1.000000e+00	NaN
FGC-FGC GSD_Zone		NaN
FGC-FGC PU	-5.218181e-02	-7.875319e-01
FGC-FGC PU_Zone	-7.844645e-01	-6.123724e-01
FGC-FGC SRL	1.004404e-01	-5.749792e-01
FGC-FGC SRL_Zone	8.006408e-02	-6.666667e-01
FGC-FGC SRR	2.629619e-01	-7.158291e-01
FGC-FGC SRR_Zone	8.006408e-02	-6.666667e-01
FGC-FGC TL	1.000000e+00	8.006408e-02
FGC-FGC TL_Zone	8.006408e-02	1.000000e+00
BIA-BIA_Activity_Level_num	-1.922963e-16	5.000000e-01
BIA-BIA_BMC	9.728373e-01	-7.267570e-01
BIA-BIA_BMI	9.103617e-01	-9.953031e-01
BIA-BIA_BMR	9.999996e-01	-8.664655e-01
BIA-BIA_DEE	9.251778e-01	-6.114604e-01
BIA-BIA_ECW	9.821499e-01	-9.446167e-01
BIA-BIA_FFM	9.999996e-01	-8.664556e-01
BIA-BIA_FFMI	9.035463e-01	-9.967393e-01
BIA-BIA_FMI	9.122150e-01	-9.948573e-01
BIA-BIA_Fat	9.321317e-01	-9.883094e-01
BIA-BIA_Frame_num	8.660254e-01	-5.000000e-01
BIA-BIA_ICW	9.733643e-01	-7.283263e-01
BIA-BIA_LDM	9.840399e-01	-7.632297e-01
BIA-BIA_LST	9.999439e-01	-8.712735e-01
BIA-BIA_SMM	9.974522e-01	-8.994880e-01
BIA-BIA_TBW	9.973791e-01	-8.999323e-01

PAQ_A-PAQ_A_Total		NaN	NaN
PAQ_C-PAQ_C_Total	8.368427e-01	-3.794303e-01	
SDS-SDS_Total_Raw	3.419928e-02	-7.453560e-01	
SDS-SDS_Total_T	2.435423e-16	-7.171372e-01	
PreInt_EduHx-computerinternet_hoursday	-7.752171e-01	-3.583229e-17	
	BIA-BIA_Activity_Level_num \		
Basic_Demos-Age	-1.922963e-16		
Basic_Demos-Sex	-5.000000e-01		
CGAS-CGAS_Score	9.991089e-01		
Physical-BMI	-2.650820e-01		
Physical-Height	2.678278e-01		
Physical-Weight	1.880616e-03		
Physical-Waist_Circumference		NaN	
Physical-Diastolic_BP		NaN	
Physical-HeartRate	1.000000e+00		
Physical-Systolic_BP	1.000000e+00		
Fitness_Endurance-Max_Stage		NaN	
Fitness_Endurance-Time_Mins		NaN	
Fitness_Endurance-Time_Sec		NaN	
FGC-FGC CU	7.559289e-01		
FGC-FGC CU_Zone	1.000000e+00		
FGC-FGC GSND		NaN	
FGC-FGC GSND_Zone		NaN	
FGC-FGC GSD		NaN	
FGC-FGC GSD_Zone		NaN	
FGC-FGC PU	3.592106e-01		
FGC-FGC PU_Zone		NaN	
FGC-FGC SRL	-5.000000e-01		
FGC-FGC SRL_Zone	-5.000000e-01		
FGC-FGC SRR	-3.273268e-01		
FGC-FGC SRR_Zone	-5.000000e-01		
FGC-FGC TL	-1.922963e-16		
FGC-FGC TL_Zone	5.000000e-01		
BIA-BIA_Activity_Level_num	1.000000e+00		
BIA-BIA_BMC	2.314897e-01		
BIA-BIA_BMI	-4.138134e-01		
BIA-BIA_BMR	-8.809372e-04		
BIA-BIA_DEE	3.795341e-01		
BIA-BIA_ECW	-1.880999e-01		
BIA-BIA_FFM	-8.610810e-04		
BIA-BIA_FFMI	-4.284905e-01		
BIA-BIA_FMI	-4.097119e-01		
BIA-BIA_Fat	-3.621194e-01		
BIA-BIA_Frame_num	5.000000e-01		
BIA-BIA_ICW	2.292639e-01		
BIA-BIA_LDM	1.779477e-01		
BIA-BIA_LST	-1.059347e-02		

BIA-BIA_SMM	-7.133819e-02		
BIA-BIA_TBW	-7.235330e-02		
PAQ_A-PAQ_A_Total	Nan		
PAQ_C-PAQ_C_Total	-1.000000e+00		
SDS-SDS_Total_Raw	-1.000000e+00		
SDS-SDS_Total_T	-1.000000e+00		
PreInt_EduHx-computerinternet_hoursday	-5.000000e-01		
		BIA-BIA_BMC	BIA-BIA_BMI
Basic_Demos-Age	0.972837	0.910362	1.000000
Basic_Demos-Sex	0.726757	0.995303	0.866466
CGAS-CGAS_Score	0.190222	-0.451869	-0.043088
Physical-BMI	0.876671	0.987489	0.964459
Physical-Height	0.999296	0.766273	0.963230
Physical-Weight	0.973271	0.909582	0.999996
Physical-Waist_Circumference	NaN	NaN	NaN
Physical-Diastolic_BP	NaN	NaN	NaN
Physical-HeartRate	-1.000000	-1.000000	-1.000000
Physical-Systolic_BP	-1.000000	-1.000000	-1.000000
Fitness_Endurance-Max_Stage	NaN	NaN	NaN
Fitness_Endurance-Time_Mins	NaN	NaN	NaN
Fitness_Endurance-Time_Sec	NaN	NaN	NaN
FGC-FGC CU	0.811861	0.283158	0.653987
FGC-FGC CU_Zone	0.231490	-0.413813	-0.000881
FGC-FGC GSND	NaN	NaN	NaN
FGC-FGC GSND_Zone	NaN	NaN	NaN
FGC-FGC GSD	NaN	NaN	NaN
FGC-FGC GSD_Zone	NaN	NaN	NaN
FGC-FGC PU	0.991060	0.700955	0.932940
FGC-FGC PU_Zone	NaN	NaN	NaN
FGC-FGC SRL	0.726757	0.995303	0.866466
FGC-FGC SRL_Zone	0.726757	0.995303	0.866466
FGC-FGC SRR	0.843472	0.995663	0.945199
FGC-FGC SRR_Zone	0.726757	0.995303	0.866466
FGC-FGC TL	0.972837	0.910362	1.000000
FGC-FGC TL_Zone	-0.726757	-0.995303	-0.866466
BIA-BIA_Activity_Level_num	0.231490	-0.413813	-0.000881
BIA-BIA_BMC	1.000000	0.789840	0.972633
BIA-BIA_BMI	0.789840	1.000000	0.910726
BIA-BIA_BMR	0.972633	0.910726	1.000000
BIA-BIA_DEE	0.987906	0.685190	0.924843
BIA-BIA_ECW	0.911929	0.971950	0.982315
BIA-BIA_FFM	0.972638	0.910718	1.000000
BIA-BIA_FFMI	0.779812	0.999869	0.903923
BIA-BIA_FMI	0.792593	0.999990	0.912576
BIA-BIA_Fat	0.822986	0.998427	0.932450
BIA-BIA_Frame_num	0.958247	0.581490	0.865585
BIA-BIA_ICW	0.999997	0.791241	0.973162

BIA-BIA_LDM	0.998504	0.822195	0.983883
BIA-BIA_LST	0.970330	0.914694	0.999953
BIA-BIA_SMM	0.953845	0.937563	0.997515
BIA-BIA_TBW	0.953539	0.937917	0.997442
PAQ_A-PAQ_A_Total	NaN	NaN	NaN
PAQ_C-PAQ_C_Total	1.000000	1.000000	1.000000
SDS-SDS_Total_Raw	1.000000	1.000000	1.000000
SDS-SDS_Total_T	1.000000	1.000000	1.000000
PreInt_EduHx-computerinternet_hoursday	-0.958247	-0.581490	-0.865585
	BIA-BIA_DEE	BIA-BIA_ECW	BIA-BIA_FFM
Basic_Demos-Age	0.925178	0.982150	1.000000
Basic_Demos-Sex	0.611460	0.944617	0.866456
CGAS-CGAS_Score	0.340146	-0.229386	-0.043068
Physical-BMI	0.791473	0.996876	0.964454
Physical-Height	0.993028	0.895890	0.963236
Physical-Weight	0.925890	0.981794	0.999996
Physical-Waist_Circumference	NaN	NaN	NaN
Physical-Diastolic_BP	NaN	NaN	NaN
Physical-HeartRate	-1.000000	-1.000000	-1.000000
Physical-Systolic_BP	-1.000000	-1.000000	-1.000000
Fitness_Endurance-Max_Stage	NaN	NaN	NaN
Fitness_Endurance-Time_Mins	NaN	NaN	NaN
Fitness_Endurance-Time_Sec	NaN	NaN	NaN
FGC-FGC CU	0.892572	0.500778	0.654003
FGC-FGC CU_Zone	0.379534	-0.188100	-0.000861
FGC-FGC GSND	NaN	NaN	NaN
FGC-FGC GSND_Zone	NaN	NaN	NaN
FGC-FGC GSD	NaN	NaN	NaN
FGC-FGC GSD_Zone	NaN	NaN	NaN
FGC-FGC PU	0.999761	0.849030	0.932947
FGC-FGC PU_Zone	NaN	NaN	NaN
FGC-FGC SRL	0.611460	0.944617	0.866456
FGC-FGC SRL_Zone	0.611460	0.944617	0.866456
FGC-FGC SRR	0.749979	0.989615	0.945193
FGC-FGC SRR_Zone	0.611460	0.944617	0.866456
FGC-FGC TL	0.925178	0.982150	1.000000
FGC-FGC TL_Zone	-0.611460	-0.944617	-0.866456
BIA-BIA_Activity_Level_num	0.379534	-0.188100	-0.000861
BIA-BIA_BMC	0.987906	0.911929	0.972638
BIA-BIA_BMI	0.685190	0.971950	0.910718
BIA-BIA_BMR	0.924843	0.982315	1.000000
BIA-BIA_DEE	1.000000	0.837273	0.924851
BIA-BIA_ECW	0.837273	1.000000	0.982312
BIA-BIA_FFM	0.924851	0.982312	1.000000
BIA-BIA_FFMI	0.673314	0.968017	0.903915
BIA-BIA_FMI	0.688461	0.972999	0.912567
BIA-BIA_Fat	0.724951	0.983608	0.932443

BIA-BIA_Frame_num	0.990994	0.756517	0.865595
BIA-BIA_ICW	0.987548	0.912865	0.973167
BIA-BIA_LDM	0.977949	0.933003	0.983886
BIA-BIA_LST	0.921105	0.984087	0.999953
BIA-BIA_SMM	0.895745	0.993066	0.997513
BIA-BIA_TBW	0.895292	0.993185	0.997441
PAQ_A-PAQ_A_Total	NaN	NaN	NaN
PAQ_C-PAQ_C_Total	1.000000	1.000000	1.000000
SDS-SDS_Total_Raw	1.000000	1.000000	1.000000
SDS-SDS_Total_T	1.000000	1.000000	1.000000
PreInt_EduHx-computerinternet_hoursday	-0.990994	-0.756517	-0.865595
	BIA-BIA_FFFMI	BIA-BIA_FMI	\
Basic_Demos-Age	0.903546	0.912215	
Basic_Demos-Sex	0.996739	0.994857	
CGAS-CGAS_Score	-0.466245	-0.447849	
Physical-BMI	0.984808	0.988189	
Physical-Height	0.755775	0.769157	
Physical-Weight	0.902739	0.911443	
Physical-Waist_Circumference	NaN	NaN	
Physical-Diastolic_BP	NaN	NaN	
Physical-HeartRate	-1.000000	-1.000000	
Physical-Systolic_BP	-1.000000	-1.000000	
Fitness_Endurance-Max_Stage	NaN	NaN	
Fitness_Endurance-Time_Mins	NaN	NaN	
Fitness_Endurance-Time_Sec	NaN	NaN	
FGC-FGC CU	0.267602	0.287472	
FGC-FGC CU_Zone	-0.428490	-0.409712	
FGC-FGC GSND	NaN	NaN	
FGC-FGC GSND_Zone	NaN	NaN	
FGC-FGC GSD	NaN	NaN	
FGC-FGC GSD_Zone	NaN	NaN	
FGC-FGC PU	0.689322	0.704158	
FGC-FGC PU_Zone	NaN	NaN	
FGC-FGC SRL	0.996739	0.994857	
FGC-FGC SRL_Zone	0.996739	0.994857	
FGC-FGC SRR	0.994027	0.996072	
FGC-FGC SRR_Zone	0.996739	0.994857	
FGC-FGC TL	0.903546	0.912215	
FGC-FGC TL_Zone	-0.996739	-0.994857	
BIA-BIA_Activity_Level_num	-0.428490	-0.409712	
BIA-BIA_BMC	0.779812	0.792593	
BIA-BIA_BMI	0.999869	0.999990	
BIA-BIA_BMR	0.903923	0.912576	
BIA-BIA_DEE	0.673314	0.688461	
BIA-BIA_ECW	0.968017	0.972999	
BIA-BIA_FFM	0.903915	0.912567	
BIA-BIA_FFFMI	1.000000	0.999786	

BIA-BIA_FMI	0.999786	1.000000
BIA-BIA_Fat	0.997389	0.998669
BIA-BIA_Frame_num	0.568249	0.585145
BIA-BIA_ICW	0.781242	0.793985
BIA-BIA_LDM	0.812877	0.824749
BIA-BIA_LST	0.908035	0.916504
BIA-BIA_SMM	0.931812	0.939119
BIA-BIA_TBW	0.932181	0.939468
PAQ_A-PAQ_A_Total	NaN	NaN
PAQ_C-PAQ_C_Total	1.000000	1.000000
SDS-SDS_Total_Raw	1.000000	1.000000
SDS-SDS_Total_T	1.000000	1.000000
PreInt_EduHx-computerinternet_hoursday	-0.568249	-0.585145

	BIA-BIA_Fat	BIA-BIA_Frame_num	\
Basic_Demos-Age	0.932132	0.866025	
Basic_Demos-Sex	0.988309	0.500000	
CGAS-CGAS_Score	-0.401140	0.463002	
Physical-BMI	0.994777	0.702503	
Physical-Height	0.801092	0.968301	
Physical-Weight	0.931449	0.866964	
Physical-Waist_Circumference	NaN	NaN	
Physical-Diastolic_BP	NaN	NaN	
Physical-HeartRate	-1.000000	NaN	
Physical-Systolic_BP	-1.000000	NaN	
Fitness_Endurance-Max_Stage	NaN	NaN	
Fitness_Endurance-Time_Mins	NaN	NaN	
Fitness_Endurance-Time_Sec	NaN	NaN	
FGC-FGC CU	0.336487	0.944911	
FGC-FGC CU_Zone	-0.362119	0.500000	
FGC-FGC GSND	NaN	NaN	
FGC-FGC GSND_Zone	NaN	NaN	
FGC-FGC GSD	NaN	NaN	
FGC-FGC GSD_Zone	NaN	NaN	
FGC-FGC PU	0.739841	0.987829	
FGC-FGC PU_Zone	NaN	NaN	
FGC-FGC SRL	0.988309	0.500000	
FGC-FGC SRL_Zone	0.988309	0.500000	
FGC-FGC SRR	0.999313	0.654654	
FGC-FGC SRR_Zone	0.988309	0.500000	
FGC-FGC TL	0.932132	0.866025	
FGC-FGC TL_Zone	-0.988309	-0.500000	
BIA-BIA_Activity_Level_num	-0.362119	0.500000	
BIA-BIA_BMC	0.822986	0.958247	
BIA-BIA_BMI	0.998427	0.581490	
BIA-BIA_BMR	0.932450	0.865585	
BIA-BIA_DEE	0.724951	0.990994	
BIA-BIA_ECW	0.983608	0.756517	

BIA-BIA_FFM	0.932443	0.865595		
BIA-BIA_FFFM	0.997389	0.568249		
BIA-BIA_FMI	0.998669	0.585145		
BIA-BIA_Fat	1.000000	0.626190		
BIA-BIA_Frame_num	0.626190	1.000000		
BIA-BIA_ICW	0.824283	0.957590		
BIA-BIA_LDM	0.852817	0.941177		
BIA-BIA_LST	0.935916	0.860680		
BIA-BIA_SMM	0.955590	0.828150		
BIA-BIA_TBW	0.955889	0.827579		
PAQ_A-PAQ_A_Total	NaN	NaN		
PAQ_C-PAQ_C_Total	1.000000	NaN		
SDS-SDS_Total_Raw	1.000000	NaN		
SDS-SDS_Total_T	1.000000	NaN		
PreInt_EduHx-computerinternet_hoursday	-0.626190	-1.000000		
	BIA-BIA_ICW	BIA-BIA_LDM	BIA-BIA_LST	\
Basic_Demos-Age	0.973364	0.984040	0.999944	
Basic_Demos-Sex	0.728326	0.763230	0.871274	
CGAS-CGAS_Score	0.187976	0.136255	-0.052789	
Physical-BMI	0.877769	0.901666	0.966980	
Physical-Height	0.999207	0.995749	0.960575	
Physical-Weight	0.973794	0.984373	0.999922	
Physical-Waist_Circumference	NaN	NaN	NaN	
Physical-Diastolic_BP	NaN	NaN	NaN	
Physical-HeartRate	-1.000000	-1.000000	-1.000000	
Physical-Systolic_BP	-1.000000	-1.000000	-1.000000	
Fitness_Endurance-Max_Stage	NaN	NaN	NaN	
Fitness_Endurance-Time_Mins	NaN	NaN	NaN	
Fitness_Endurance-Time_Sec	NaN	NaN	NaN	
FGC-FGC CU	0.810524	0.778721	0.646609	
FGC-FGC CU_Zone	0.229264	0.177948	-0.010593	
FGC-FGC GSND	NaN	NaN	NaN	
FGC-FGC GSND_Zone	NaN	NaN	NaN	
FGC-FGC GSD	NaN	NaN	NaN	
FGC-FGC GSD_Zone	NaN	NaN	NaN	
FGC-FGC PU	0.990753	0.982282	0.929399	
FGC-FGC PU_Zone	NaN	NaN	NaN	
FGC-FGC SRL	0.728326	0.763230	0.871274	
FGC-FGC SRL_Zone	0.728326	0.763230	0.871274	
FGC-FGC SRR	0.844699	0.871583	0.948326	
FGC-FGC SRR_Zone	0.728326	0.763230	0.871274	
FGC-FGC TL	0.973364	0.984040	0.999944	
FGC-FGC TL_Zone	-0.728326	-0.763230	-0.871274	
BIA-BIA_Activity_Level_num	0.229264	0.177948	-0.010593	
BIA-BIA_BMC	0.999997	0.998504	0.970330	
BIA-BIA_BMI	0.791241	0.822195	0.914694	
BIA-BIA_BMR	0.973162	0.983883	0.999953	

BIA-BIA_DEE	0.987548	0.977949	0.921105
BIA-BIA_ECW	0.912865	0.933003	0.984087
BIA-BIA_FFM	0.973167	0.983886	0.999953
BIA-BIA_FFMI	0.781242	0.812877	0.908035
BIA-BIA_FMI	0.793985	0.824749	0.916504
BIA-BIA_Fat	0.824283	0.852817	0.935916
BIA-BIA_Frame_num	0.957590	0.941177	0.860680
BIA-BIA_ICW	1.000000	0.998626	0.970881
BIA-BIA_LDM	0.998626	1.000000	0.982100
BIA-BIA_LST	0.970881	0.982100	1.000000
BIA-BIA_SMM	0.954529	0.968838	0.998152
BIA-BIA_TBW	0.954225	0.968586	0.998090
PAQ_A-PAQ_A_Total	NaN	NaN	NaN
PAQ_C-PAQ_C_Total	1.000000	1.000000	1.000000
SDS-SDS_Total_Raw	1.000000	1.000000	1.000000
SDS-SDS_Total_T	1.000000	1.000000	1.000000
PreInt_EduHx-computerinternet_hoursday	-0.957590	-0.941177	-0.860680

	BIA-BIA_SMM	BIA-BIA_TBW	\
Basic_Demos-Age	0.997452	0.997379	
Basic_Demos-Sex	0.899488	0.899932	
CGAS-CGAS_Score	-0.113375	-0.114386	
Physical-BMI	0.980680	0.980878	
Physical-Height	0.941906	0.941563	
Physical-Weight	0.997316	0.997241	
Physical-Waist_Circumference	NaN	NaN	
Physical-Diastolic_BP	NaN	NaN	
Physical-HeartRate	-1.000000	-1.000000	
Physical-Systolic_BP	-1.000000	-1.000000	
Fitness_Endurance-Max_Stage	NaN	NaN	
Fitness_Endurance-Time_Mins	NaN	NaN	
Fitness_Endurance-Time_Sec	NaN	NaN	
FGC-FGC CU	0.599059	0.598244	
FGC-FGC CU_Zone	-0.071338	-0.072353	
FGC-FGC GSND	NaN	NaN	
FGC-FGC GSND_Zone	NaN	NaN	
FGC-FGC GSD	NaN	NaN	
FGC-FGC GSD_Zone	NaN	NaN	
FGC-FGC PU	0.905253	0.904820	
FGC-FGC PU_Zone	NaN	NaN	
FGC-FGC SRL	0.899488	0.899932	
FGC-FGC SRL_Zone	0.899488	0.899932	
FGC-FGC SRR	0.965855	0.966118	
FGC-FGC SRR_Zone	0.899488	0.899932	
FGC-FGC TL	0.997452	0.997379	
FGC-FGC TL_Zone	-0.899488	-0.899932	
BIA-BIA_Activity_Level_num	-0.071338	-0.072353	
BIA-BIA_BMC	0.953845	0.953539	

BIA-BIA_BMI	0.937563	0.937917
BIA-BIA_BMR	0.997515	0.997442
BIA-BIA_DEE	0.895745	0.895292
BIA-BIA_ECW	0.993066	0.993185
BIA-BIA_FFM	0.997513	0.997441
BIA-BIA_FFFI	0.931812	0.932181
BIA-BIA_FMI	0.939119	0.939468
BIA-BIA_Fat	0.955590	0.955889
BIA-BIA_Frame_num	0.828150	0.827579
BIA-BIA_ICW	0.954529	0.954225
BIA-BIA_LDM	0.968838	0.968586
BIA-BIA_LST	0.998152	0.998090
BIA-BIA_SMM	1.000000	0.999999
BIA-BIA_TBW	0.999999	1.000000
PAQ_A-PAQ_A_Total	NaN	NaN
PAQ_C-PAQ_C_Total	1.000000	1.000000
SDS-SDS_Total_Raw	1.000000	1.000000
SDS-SDS_Total_T	1.000000	1.000000
PreInt_EduHx-computerinternet_hoursday	-0.828150	-0.827579

	PAQ_A-PAQ_A_Total	PAQ_C-PAQ_C_Total	\
Basic_Demos-Age	NaN	0.564902	
Basic_Demos-Sex	NaN	0.632346	
CGAS-CGAS_Score	NaN	-0.750481	
Physical-BMI	NaN	0.988267	
Physical-Height	NaN	0.964600	
Physical-Weight	NaN	0.999819	
Physical-Waist_Circumference	NaN	NaN	
Physical-Diastolic_BP	NaN	-0.611549	
Physical-HeartRate	NaN	-0.969066	
Physical-Systolic_BP	NaN	-0.990979	
Fitness_Endurance-Max_Stage	NaN	1.000000	
Fitness_Endurance-Time_Mins	NaN	1.000000	
Fitness_Endurance-Time_Sec	NaN	1.000000	
FGC-FGC CU	NaN	-0.994158	
FGC-FGC CU_Zone	NaN	-0.990979	
FGC-FGC GSND	NaN	1.000000	
FGC-FGC GSND_Zone	NaN	1.000000	
FGC-FGC GSD	NaN	1.000000	
FGC-FGC GSD_Zone	NaN	NaN	
FGC-FGC PU	NaN	-0.134014	
FGC-FGC PU_Zone	NaN	-0.611549	
FGC-FGC SRL	NaN	0.379430	
FGC-FGC SRL_Zone	NaN	0.379430	
FGC-FGC SRR	NaN	0.590553	
FGC-FGC SRR_Zone	NaN	0.379430	
FGC-FGC TL	NaN	0.836843	
FGC-FGC TL_Zone	NaN	-0.379430	

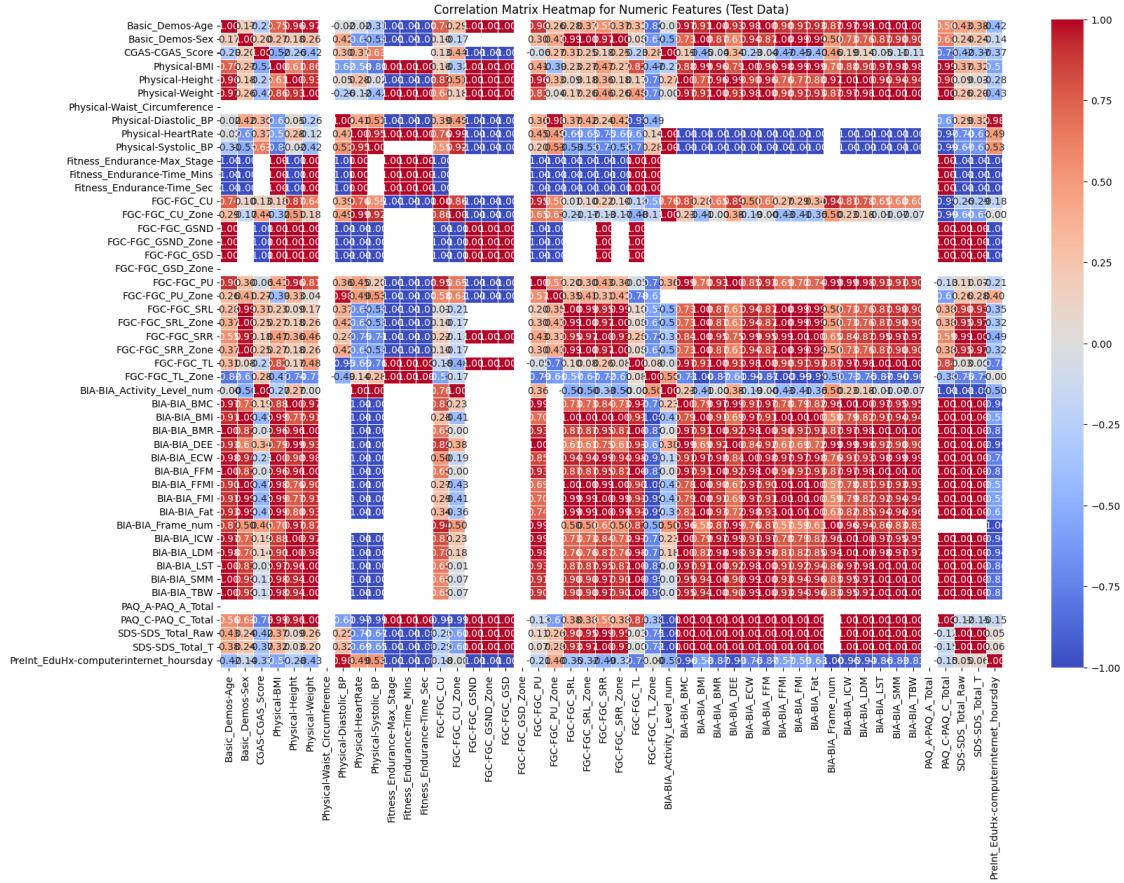
BIA-BIA_Activity_Level_num	NaN	-1.000000
BIA-BIA_BMC	NaN	1.000000
BIA-BIA_BMI	NaN	1.000000
BIA-BIA_BMR	NaN	1.000000
BIA-BIA_DEE	NaN	1.000000
BIA-BIA_ECW	NaN	1.000000
BIA-BIA_FFM	NaN	1.000000
BIA-BIA_FFFI	NaN	1.000000
BIA-BIA_FMI	NaN	1.000000
BIA-BIA_Fat	NaN	1.000000
BIA-BIA_Frame_num	NaN	NaN
BIA-BIA_ICW	NaN	1.000000
BIA-BIA_LDM	NaN	1.000000
BIA-BIA_LST	NaN	1.000000
BIA-BIA_SMM	NaN	1.000000
BIA-BIA_TBW	NaN	1.000000
PAQ_A-PAQ_A_Total	NaN	NaN
PAQ_C-PAQ_C_Total	NaN	1.000000
SDS-SDS_Total_Raw	NaN	-0.116212
SDS-SDS_Total_T	NaN	-0.151963
PreInt_EduHx-computerinternet_hoursday	NaN	-0.153981

	SDS-SDS_Total_Raw	SDS-SDS_Total_T \
Basic_Demos-Age	0.429548	3.838790e-01
Basic_Demos-Sex	0.241423	2.445998e-01
CGAS-CGAS_Score	-0.422847	-3.729518e-01
Physical-BMI	0.374065	3.181555e-01
Physical-Height	0.088035	3.025061e-02
Physical-Weight	0.263425	1.989699e-01
Physical-Waist_Circumference	NaN	NaN
Physical-Diastolic_BP	0.289241	3.188741e-01
Physical-HeartRate	-0.695701	-6.930265e-01
Physical-Systolic_BP	-0.672726	-6.491665e-01
Fitness_Endurance-Max_Stage	-1.000000	-1.000000e+00
Fitness_Endurance-Time_Mins	-1.000000	-1.000000e+00
Fitness_Endurance-Time_Sec	-1.000000	-1.000000e+00
FGC-FGC CU	-0.258199	-2.913610e-01
FGC-FGC CU_Zone	-0.596285	-5.976143e-01
FGC-FGC GSND	1.000000	1.000000e+00
FGC-FGC GSND_Zone	1.000000	1.000000e+00
FGC-FGC GSD	1.000000	1.000000e+00
FGC-FGC GSD_Zone	NaN	NaN
FGC-FGC PU	0.110727	6.658451e-02
FGC-FGC PU_Zone	0.258199	2.760262e-01
FGC-FGC SRL	0.900567	9.268232e-01
FGC-FGC SRL_Zone	0.946729	9.660918e-01
FGC-FGC SRR	0.993808	9.960238e-01
FGC-FGC SRR_Zone	0.946729	9.660918e-01

FGC-FGC_TL	0.034199	2.435423e-16
FGC-FGC_TL_Zone	-0.745356	-7.171372e-01
BIA-BIA_Activity_Level_num	-1.000000	-1.000000e+00
BIA-BIA_BMC	1.000000	1.000000e+00
BIA-BIA_BMI	1.000000	1.000000e+00
BIA-BIA_BMR	1.000000	1.000000e+00
BIA-BIA_DEE	1.000000	1.000000e+00
BIA-BIA_ECW	1.000000	1.000000e+00
BIA-BIA_FFM	1.000000	1.000000e+00
BIA-BIA_FFFI	1.000000	1.000000e+00
BIA-BIA_FMI	1.000000	1.000000e+00
BIA-BIA_Fat	1.000000	1.000000e+00
BIA-BIA_Frame_num	NaN	NaN
BIA-BIA_ICW	1.000000	1.000000e+00
BIA-BIA_LDM	1.000000	1.000000e+00
BIA-BIA_LST	1.000000	1.000000e+00
BIA-BIA_SMM	1.000000	1.000000e+00
BIA-BIA_TBW	1.000000	1.000000e+00
PAQ_A-PAQ_A_Total	NaN	NaN
PAQ_C-PAQ_C_Total	-0.116212	-1.519632e-01
SDS-SDS_Total_Raw	1.000000	9.985168e-01
SDS-SDS_Total_T	0.998517	1.000000e+00
PreInt_EduHx-computerinternet_hoursday	0.053760	6.419407e-02

	PreInt_EduHx-computerinternet_hoursday	
Basic_Demos-Age		-4.243216e-01
Basic_Demos-Sex		-1.373606e-01
CGAS-CGAS_Score		-3.660247e-01
Physical-BMI		-5.667507e-01
Physical-Height		-2.808902e-01
Physical-Weight		-4.325382e-01
Physical-Waist_Circumference		NaN
Physical-Diastolic_BP		9.801961e-01
Physical-HeartRate		4.898979e-01
Physical-Systolic_BP		5.303144e-01
Fitness_Endurance-Max_Stage		-1.000000e+00
Fitness_Endurance-Time_Mins		-1.000000e+00
Fitness_Endurance-Time_Sec		-1.000000e+00
FGC-FGC CU		-1.843024e-01
FGC-FGC CU_Zone		-7.166459e-17
FGC-FGC_GSND		-1.000000e+00
FGC-FGC_GSND_Zone		-1.000000e+00
FGC-FGC_GSD		-1.000000e+00
FGC-FGC_GSD_Zone		NaN
FGC-FGC_PU		-2.103516e-01
FGC-FGC_PU_Zone		3.952847e-01
FGC-FGC_SRL		-3.542771e-01
FGC-FGC_SRL_Zone		-3.227486e-01

FGC-FGC_SRR	-4.892461e-01
FGC-FGC_SRR_Zone	-3.227486e-01
FGC-FGC_TL	-7.752171e-01
FGC-FGC_TL_Zone	-3.583229e-17
BIA-BIA_Activity_Level_num	-5.000000e-01
BIA-BIA_BMC	-9.582467e-01
BIA-BIA_BMI	-5.814897e-01
BIA-BIA_BMR	-8.655846e-01
BIA-BIA_DEE	-9.909945e-01
BIA-BIA_ECW	-7.565168e-01
BIA-BIA_FFM	-8.655945e-01
BIA-BIA_FFMI	-5.682488e-01
BIA-BIA_FMI	-5.851454e-01
BIA-BIA_Fat	-6.261901e-01
BIA-BIA_Frame_num	-1.000000e+00
BIA-BIA_ICW	-9.575901e-01
BIA-BIA_LDM	-9.411774e-01
BIA-BIA_LST	-8.606801e-01
BIA-BIA_SMM	-8.281498e-01
BIA-BIA_TBW	-8.275790e-01
PAQ_A-PAQ_A_Total	NaN
PAQ_C-PAQ_C_Total	-1.539806e-01
SDS-SDS_Total_Raw	5.376033e-02
SDS-SDS_Total_T	6.419407e-02
PreInt_EduHx-computerinternet_hoursday	1.000000e+00



Highly Correlated Pairs in Test Data ($|correlation| > 0.8$):

Feature 1: Basic_Demos-Age, Feature 2: Physical-Height, Correlation: 0.96

Feature 1: Basic_Demos-Age, Feature 2: Physical-Weight, Correlation: 0.97

Feature 1: Basic_Demos-Age, Feature 2: Fitness_Endurance-Max_Stage, Correlation: -1.00

Feature 1: Basic_Demos-Age, Feature 2: Fitness_Endurance-Time_Mins, Correlation: -1.00

Feature 1: Basic_Demos-Age, Feature 2: Fitness_Endurance-Time_Sec, Correlation: -1.00

Feature 1: Basic Demos-Age Feature 2: ECG-ECG GSND Correlation: 1.00

Feature 1: Basic_Demos_Age, Feature 2: FCC-FCC_GSND, Correlation: 1.00
Feature 1: Basic_Demos_Age, Feature 2: FCC-GCC_GSND, Correlation: 1.00

Feature 1: Basic_Demos_Age, Feature 2: FCG_FCG_GEND_ZONE, Correlation: 1.000

Feature 1: Basic_Demos_Age, Feature 2: FGS_FGS_GSB, Correlation: 1.00

Feature 1: Basic_Demos_Age, Feature 2: FCG_FCG_FC, Correlation: 0.99
Feature 1: Basic_Demos_Age, Feature 2: ECG-ECG_TI_Zero, Correlation: -0.82

Feature 1: Basic_Demos_Age, Feature 2: RGA_RGA_TE_ZONE, Correlation: 0.97

Feature 1: Basic_Demos_Age, Feature 2: BIA_BIA_BMI, Correlation: 0.91

Feature 1: Basic_Demos_Age, Feature 2: BIA_BIA_BMI, Correlation: 0.31

Feature 1: Basic_Demos_Age, Feature 2: BIA_BIA_BTW, Correlation: 1.00

Feature 1: Basic_Demos_Age, Feature 2: BIA_BIA_DEL, Correlation: 0.35

Feature 1: Basic_Demos_Age, Feature 2: BIA-BIA_ECW, Correlation: 0.99

Feature 1: Basic_Demos-Age, Feature 2: BIA-BIA_FFM, Correlation: 1.00
 Feature 1: Basic_Demos-Age, Feature 2: BIA-BIA_FFFMI, Correlation: 0.90
 Feature 1: Basic_Demos-Age, Feature 2: BIA-BIA_FMI, Correlation: 0.91
 Feature 1: Basic_Demos-Age, Feature 2: BIA-BIA_Fat, Correlation: 0.93
 Feature 1: Basic_Demos-Age, Feature 2: BIA-BIA_Frame_num, Correlation: 0.87
 Feature 1: Basic_Demos-Age, Feature 2: BIA-BIA_ICW, Correlation: 0.97
 Feature 1: Basic_Demos-Age, Feature 2: BIA-BIA_LDM, Correlation: 0.98
 Feature 1: Basic_Demos-Age, Feature 2: BIA-BIA_LST, Correlation: 1.00
 Feature 1: Basic_Demos-Age, Feature 2: BIA-BIA_SMM, Correlation: 1.00
 Feature 1: Basic_Demos-Age, Feature 2: BIA-BIA_TBW, Correlation: 1.00
 Feature 1: Basic_Demos-Sex, Feature 2: Fitness_Endurance-Max_Stage, Correlation: -1.00
 Feature 1: Basic_Demos-Sex, Feature 2: Fitness_Endurance-Time_Mins, Correlation: -1.00
 Feature 1: Basic_Demos-Sex, Feature 2: Fitness_Endurance-Time_Sec, Correlation: -1.00
 Feature 1: Basic_Demos-Sex, Feature 2: FGC-FGC_SRL, Correlation: 0.99
 Feature 1: Basic_Demos-Sex, Feature 2: FGC-FGC_SRL_Zone, Correlation: 1.00
 Feature 1: Basic_Demos-Sex, Feature 2: FGC-FGC_SRR, Correlation: 0.97
 Feature 1: Basic_Demos-Sex, Feature 2: FGC-FGC_SRR_Zone, Correlation: 1.00
 Feature 1: Basic_Demos-Sex, Feature 2: BIA-BIA_BMI, Correlation: 1.00
 Feature 1: Basic_Demos-Sex, Feature 2: BIA-BIA_BMR, Correlation: 0.87
 Feature 1: Basic_Demos-Sex, Feature 2: BIA-BIA_ECW, Correlation: 0.94
 Feature 1: Basic_Demos-Sex, Feature 2: BIA-BIA_FFM, Correlation: 0.87
 Feature 1: Basic_Demos-Sex, Feature 2: BIA-BIA_FFFMI, Correlation: 1.00
 Feature 1: Basic_Demos-Sex, Feature 2: BIA-BIA_FMI, Correlation: 0.99
 Feature 1: Basic_Demos-Sex, Feature 2: BIA-BIA_Fat, Correlation: 0.99
 Feature 1: Basic_Demos-Sex, Feature 2: BIA-BIA_LST, Correlation: 0.87
 Feature 1: Basic_Demos-Sex, Feature 2: BIA-BIA_SMM, Correlation: 0.90
 Feature 1: Basic_Demos-Sex, Feature 2: BIA-BIA_TBW, Correlation: 0.90
 Feature 1: CGAS-CGAS_Score, Feature 2: FGC-FGC_GSND, Correlation: -1.00
 Feature 1: CGAS-CGAS_Score, Feature 2: FGC-FGC_GSND_Zone, Correlation: -1.00
 Feature 1: CGAS-CGAS_Score, Feature 2: FGC-FGC_GSD, Correlation: -1.00
 Feature 1: CGAS-CGAS_Score, Feature 2: BIA-BIA_Activity_Level_num, Correlation: 1.00
 Feature 1: Physical-BMI, Feature 2: Physical-Weight, Correlation: 0.86
 Feature 1: Physical-BMI, Feature 2: Physical-Systolic_BP, Correlation: -0.80
 Feature 1: Physical-BMI, Feature 2: Fitness_Endurance-Max_Stage, Correlation: 1.00
 Feature 1: Physical-BMI, Feature 2: Fitness_Endurance-Time_Mins, Correlation: 1.00
 Feature 1: Physical-BMI, Feature 2: Fitness_Endurance-Time_Sec, Correlation: 1.00
 Feature 1: Physical-BMI, Feature 2: FGC-FGC_GSND, Correlation: 1.00
 Feature 1: Physical-BMI, Feature 2: FGC-FGC_GSND_Zone, Correlation: 1.00
 Feature 1: Physical-BMI, Feature 2: FGC-FGC_GSD, Correlation: 1.00
 Feature 1: Physical-BMI, Feature 2: FGC-FGC_TL, Correlation: 0.82
 Feature 1: Physical-BMI, Feature 2: BIA-BIA_BMC, Correlation: 0.88

Feature 1: Physical-BMI, Feature 2: BIA-BIA_BMI, Correlation: 0.99
Feature 1: Physical-BMI, Feature 2: BIA-BIA_BMR, Correlation: 0.96
Feature 1: Physical-BMI, Feature 2: BIA-BIA_ECW, Correlation: 1.00
Feature 1: Physical-BMI, Feature 2: BIA-BIA_FFM, Correlation: 0.96
Feature 1: Physical-BMI, Feature 2: BIA-BIA_FFM, Correlation: 0.98
Feature 1: Physical-BMI, Feature 2: BIA-BIA_FMI, Correlation: 0.99
Feature 1: Physical-BMI, Feature 2: BIA-BIA_Fat, Correlation: 0.99
Feature 1: Physical-BMI, Feature 2: BIA-BIA_ICW, Correlation: 0.88
Feature 1: Physical-BMI, Feature 2: BIA-BIA_LDM, Correlation: 0.90
Feature 1: Physical-BMI, Feature 2: BIA-BIA_LST, Correlation: 0.97
Feature 1: Physical-BMI, Feature 2: BIA-BIA_SMM, Correlation: 0.98
Feature 1: Physical-BMI, Feature 2: BIA-BIA_TBW, Correlation: 0.98
Feature 1: Physical-BMI, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 0.99
Feature 1: Physical-Height, Feature 2: Physical-Weight, Correlation: 0.93
Feature 1: Physical-Height, Feature 2: Fitness_Endurance-Max_Stage, Correlation: -1.00
Feature 1: Physical-Height, Feature 2: Fitness_Endurance-Time_Mins, Correlation: -1.00
Feature 1: Physical-Height, Feature 2: Fitness_Endurance-Time_Sec, Correlation: -1.00
Feature 1: Physical-Height, Feature 2: FGC-FGC CU, Correlation: 0.87
Feature 1: Physical-Height, Feature 2: FGC-FGC_GSND, Correlation: 1.00
Feature 1: Physical-Height, Feature 2: FGC-FGC_GSND_Zone, Correlation: 1.00
Feature 1: Physical-Height, Feature 2: FGC-FGC_GSD, Correlation: 1.00
Feature 1: Physical-Height, Feature 2: FGC-FGC_PU, Correlation: 0.96
Feature 1: Physical-Height, Feature 2: BIA-BIA_BMC, Correlation: 1.00
Feature 1: Physical-Height, Feature 2: BIA-BIA_BMR, Correlation: 0.96
Feature 1: Physical-Height, Feature 2: BIA-BIA_DEE, Correlation: 0.99
Feature 1: Physical-Height, Feature 2: BIA-BIA_ECW, Correlation: 0.90
Feature 1: Physical-Height, Feature 2: BIA-BIA_FFM, Correlation: 0.96
Feature 1: Physical-Height, Feature 2: BIA-BIA_Fat, Correlation: 0.80
Feature 1: Physical-Height, Feature 2: BIA-BIA_Frame_num, Correlation: 0.97
Feature 1: Physical-Height, Feature 2: BIA-BIA_ICW, Correlation: 1.00
Feature 1: Physical-Height, Feature 2: BIA-BIA_LDM, Correlation: 1.00
Feature 1: Physical-Height, Feature 2: BIA-BIA_LST, Correlation: 0.96
Feature 1: Physical-Height, Feature 2: BIA-BIA_SMM, Correlation: 0.94
Feature 1: Physical-Height, Feature 2: BIA-BIA_TBW, Correlation: 0.94
Feature 1: Physical-Height, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 0.96
Feature 1: Physical-Weight, Feature 2: Fitness_Endurance-Max_Stage, Correlation: 1.00
Feature 1: Physical-Weight, Feature 2: Fitness_Endurance-Time_Mins, Correlation: 1.00
Feature 1: Physical-Weight, Feature 2: Fitness_Endurance-Time_Sec, Correlation: 1.00
Feature 1: Physical-Weight, Feature 2: FGC-FGC_GSND, Correlation: 1.00
Feature 1: Physical-Weight, Feature 2: FGC-FGC_GSND_Zone, Correlation: 1.00
Feature 1: Physical-Weight, Feature 2: FGC-FGC_GSD, Correlation: 1.00
Feature 1: Physical-Weight, Feature 2: FGC-FGC_PU, Correlation: 0.81

Feature 1: Physical-Weight, Feature 2: BIA-BIA_BMC, Correlation: 0.97
Feature 1: Physical-Weight, Feature 2: BIA-BIA_BMI, Correlation: 0.91
Feature 1: Physical-Weight, Feature 2: BIA-BIA_BMR, Correlation: 1.00
Feature 1: Physical-Weight, Feature 2: BIA-BIA_DEE, Correlation: 0.93
Feature 1: Physical-Weight, Feature 2: BIA-BIA_ECW, Correlation: 0.98
Feature 1: Physical-Weight, Feature 2: BIA-BIA_FFM, Correlation: 1.00
Feature 1: Physical-Weight, Feature 2: BIA-BIA_FFMI, Correlation: 0.90
Feature 1: Physical-Weight, Feature 2: BIA-BIA_FMI, Correlation: 0.91
Feature 1: Physical-Weight, Feature 2: BIA-BIA_Fat, Correlation: 0.93
Feature 1: Physical-Weight, Feature 2: BIA-BIA_Frame_num, Correlation: 0.87
Feature 1: Physical-Weight, Feature 2: BIA-BIA_ICW, Correlation: 0.97
Feature 1: Physical-Weight, Feature 2: BIA-BIA_LDM, Correlation: 0.98
Feature 1: Physical-Weight, Feature 2: BIA-BIA_LST, Correlation: 1.00
Feature 1: Physical-Weight, Feature 2: BIA-BIA_SMM, Correlation: 1.00
Feature 1: Physical-Weight, Feature 2: BIA-BIA_TBW, Correlation: 1.00
Feature 1: Physical-Weight, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: Physical-Diastolic_BP, Feature 2: Fitness_Endurance-Max_Stage, Correlation: -1.00
Feature 1: Physical-Diastolic_BP, Feature 2: Fitness_Endurance-Time_Mins, Correlation: -1.00
Feature 1: Physical-Diastolic_BP, Feature 2: Fitness_Endurance-Time_Sec, Correlation: -1.00
Feature 1: Physical-Diastolic_BP, Feature 2: FGC-FGC_GSND, Correlation: -1.00
Feature 1: Physical-Diastolic_BP, Feature 2: FGC-FGC_GSND_Zone, Correlation: -1.00
Feature 1: Physical-Diastolic_BP, Feature 2: FGC-FGC_GSD, Correlation: -1.00
Feature 1: Physical-Diastolic_BP, Feature 2: FGC-FGC_PU_Zone, Correlation: 0.98
Feature 1: Physical-Diastolic_BP, Feature 2: FGC-FGC_TL, Correlation: -0.95
Feature 1: Physical-Diastolic_BP, Feature 2: PreInt_EduHx-computerinternet_hoursday, Correlation: 0.98
Feature 1: Physical-HeartRate, Feature 2: Physical-Systolic_BP, Correlation: 0.95
Feature 1: Physical-HeartRate, Feature 2: Fitness_Endurance-Max_Stage, Correlation: 1.00
Feature 1: Physical-HeartRate, Feature 2: Fitness_Endurance-Time_Mins, Correlation: 1.00
Feature 1: Physical-HeartRate, Feature 2: Fitness_Endurance-Time_Sec, Correlation: 1.00
Feature 1: Physical-HeartRate, Feature 2: FGC-FGC CU_Zone, Correlation: 0.99
Feature 1: Physical-HeartRate, Feature 2: FGC-FGC_GSND, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: FGC-FGC_GSND_Zone, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: FGC-FGC_GSD, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_Activity_Level_num, Correlation: 1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_BMC, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_BMI, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_BMR, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_DEE, Correlation: -1.00

Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_ECW, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_FFM, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_FFFMI, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_FMI, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_Fat, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_ICW, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_LDM, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_LST, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_SMM, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: BIA-BIA_TBW, Correlation: -1.00
Feature 1: Physical-HeartRate, Feature 2: PAQ_C-PAQ_C_Total, Correlation: -0.97
Feature 1: Physical-Systolic_BP, Feature 2: FGC-FGC CU_Zone, Correlation: 0.92
Feature 1: Physical-Systolic_BP, Feature 2: FGC-FGC GSND, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: FGC-FGC GSND_Zone, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: FGC-FGC_GSD, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_Activity_Level_num, Correlation: 1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_BMC, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_BMI, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_BMR, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_DEE, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_ECW, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_FFM, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_FFFMI, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_FMI, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_Fat, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_ICW, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_LDM, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_LST, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_SMM, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: BIA-BIA_TBW, Correlation: -1.00
Feature 1: Physical-Systolic_BP, Feature 2: PAQ_C-PAQ_C_Total, Correlation: -0.99
Feature 1: Fitness_Endurance-Max_Stage, Feature 2: Fitness_Endurance-Time_Mins, Correlation: 1.00
Feature 1: Fitness_Endurance-Max_Stage, Feature 2: Fitness_Endurance-Time_Sec, Correlation: 1.00
Feature 1: Fitness_Endurance-Max_Stage, Feature 2: FGC-FGC CU, Correlation: -1.00
Feature 1: Fitness_Endurance-Max_Stage, Feature 2: FGC-FGC PU, Correlation: -1.00
Feature 1: Fitness_Endurance-Max_Stage, Feature 2: FGC-FGC PU_Zone, Correlation: -1.00
Feature 1: Fitness_Endurance-Max_Stage, Feature 2: FGC-FGC_SRL, Correlation: -1.00
Feature 1: Fitness_Endurance-Max_Stage, Feature 2: FGC-FGC_SRL_Zone, Correlation: -1.00

Feature 1: Fitness_Endurance-Max_Stage, Feature 2: FGC-FGC_SRR, Correlation: -1.00

Feature 1: Fitness_Endurance-Max_Stage, Feature 2: FGC-FGC_SRR_Zone, Correlation: -1.00

Feature 1: Fitness_Endurance-Max_Stage, Feature 2: FGC-FGC_TL, Correlation: 1.00

Feature 1: Fitness_Endurance-Max_Stage, Feature 2: FGC-FGC_TL_Zone, Correlation: 1.00

Feature 1: Fitness_Endurance-Max_Stage, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00

Feature 1: Fitness_Endurance-Max_Stage, Feature 2: SDS-SDS_Total_Raw, Correlation: -1.00

Feature 1: Fitness_Endurance-Max_Stage, Feature 2: SDS-SDS_Total_T, Correlation: -1.00

Feature 1: Fitness_Endurance-Max_Stage, Feature 2: PreInt_EduHx-computerinternet_hoursday, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: Fitness_Endurance-Time_Sec, Correlation: 1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: FGC-FGC CU, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: FGC-FGC PU, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: FGC-FGC PU_Zone, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: FGC-FGC_SRL, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: FGC-FGC_SRL_Zone, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: FGC-FGC_SRR, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: FGC-FGC_SRR_Zone, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: FGC-FGC_TL, Correlation: 1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: FGC-FGC_TL_Zone, Correlation: 1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: SDS-SDS_Total_Raw, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: SDS-SDS_Total_T, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Mins, Feature 2: PreInt_EduHx-computerinternet_hoursday, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Sec, Feature 2: FGC-FGC CU, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Sec, Feature 2: FGC-FGC PU, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Sec, Feature 2: FGC-FGC PU_Zone, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Sec, Feature 2: FGC-FGC_SRL, Correlation: -1.00

Feature 1: Fitness_Endurance-Time_Sec, Feature 2: FGC-FGC_SRL_Zone, Correlation: -1.00
 Feature 1: Fitness_Endurance-Time_Sec, Feature 2: FGC-FGC_SRR, Correlation: -1.00
 Feature 1: Fitness_Endurance-Time_Sec, Feature 2: FGC-FGC_SRR_Zone, Correlation: -1.00
 Feature 1: Fitness_Endurance-Time_Sec, Feature 2: FGC-FGC_TL, Correlation: 1.00
 Feature 1: Fitness_Endurance-Time_Sec, Feature 2: FGC-FGC_TL_Zone, Correlation: 1.00
 Feature 1: Fitness_Endurance-Time_Sec, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
 Feature 1: Fitness_Endurance-Time_Sec, Feature 2: SDS-SDS_Total_Raw, Correlation: -1.00
 Feature 1: Fitness_Endurance-Time_Sec, Feature 2: SDS-SDS_Total_T, Correlation: -1.00
 Feature 1: Fitness_Endurance-Time_Sec, Feature 2: PreInt_EduHx-computerinternet_hoursday, Correlation: -1.00
 Feature 1: FGC-FGC CU, Feature 2: FGC-FGC CU_Zone, Correlation: 0.86
 Feature 1: FGC-FGC CU, Feature 2: FGC-FGC GSND, Correlation: -1.00
 Feature 1: FGC-FGC CU, Feature 2: FGC-FGC GSND_Zone, Correlation: -1.00
 Feature 1: FGC-FGC CU, Feature 2: FGC-FGC GSD, Correlation: -1.00
 Feature 1: FGC-FGC CU, Feature 2: FGC-FGC PU, Correlation: 0.95
 Feature 1: FGC-FGC CU, Feature 2: BIA-BIA_BMC, Correlation: 0.81
 Feature 1: FGC-FGC CU, Feature 2: BIA-BIA_DEE, Correlation: 0.89
 Feature 1: FGC-FGC CU, Feature 2: BIA-BIA_Frame_num, Correlation: 0.94
 Feature 1: FGC-FGC CU, Feature 2: BIA-BIA_ICW, Correlation: 0.81
 Feature 1: FGC-FGC CU, Feature 2: PAQ_C-PAQ_C_Total, Correlation: -0.99
 Feature 1: FGC-FGC CU_Zone, Feature 2: FGC-FGC GSND, Correlation: -1.00
 Feature 1: FGC-FGC CU_Zone, Feature 2: FGC-FGC GSND_Zone, Correlation: -1.00
 Feature 1: FGC-FGC CU_Zone, Feature 2: FGC-FGC GSD, Correlation: -1.00
 Feature 1: FGC-FGC CU_Zone, Feature 2: BIA-BIA_Activity_Level_num, Correlation: 1.00
 Feature 1: FGC-FGC CU_Zone, Feature 2: PAQ_C-PAQ_C_Total, Correlation: -0.99
 Feature 1: FGC-FGC GSND, Feature 2: FGC-FGC GSND_Zone, Correlation: 1.00
 Feature 1: FGC-FGC GSND, Feature 2: FGC-FGC GSD, Correlation: 1.00
 Feature 1: FGC-FGC GSND, Feature 2: FGC-FGC PU, Correlation: -1.00
 Feature 1: FGC-FGC GSND, Feature 2: FGC-FGC PU_Zone, Correlation: -1.00
 Feature 1: FGC-FGC GSND, Feature 2: FGC-FGC SRR, Correlation: 1.00
 Feature 1: FGC-FGC GSND, Feature 2: FGC-FGC TL, Correlation: 1.00
 Feature 1: FGC-FGC GSND, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
 Feature 1: FGC-FGC GSND, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
 Feature 1: FGC-FGC GSND, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
 Feature 1: FGC-FGC GSND, Feature 2: PreInt_EduHx-computerinternet_hoursday, Correlation: -1.00
 Feature 1: FGC-FGC GSND_Zone, Feature 2: FGC-FGC GSD, Correlation: 1.00
 Feature 1: FGC-FGC GSND_Zone, Feature 2: FGC-FGC PU, Correlation: -1.00
 Feature 1: FGC-FGC GSND_Zone, Feature 2: FGC-FGC PU_Zone, Correlation: -1.00
 Feature 1: FGC-FGC GSND_Zone, Feature 2: FGC-FGC SRR, Correlation: 1.00

Feature 1: FGC-FGC_GSND_Zone, Feature 2: FGC-FGC_TL, Correlation: 1.00
 Feature 1: FGC-FGC_GSND_Zone, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
 Feature 1: FGC-FGC_GSND_Zone, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
 Feature 1: FGC-FGC_GSND_Zone, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
 Feature 1: FGC-FGC_GSND_Zone, Feature 2: PreInt_EduHx-computerinternet_hoursday, Correlation: -1.00
 Feature 1: FGC-FGC_GSD, Feature 2: FGC-FGC_PU, Correlation: -1.00
 Feature 1: FGC-FGC_GSD, Feature 2: FGC-FGC_PU_Zone, Correlation: -1.00
 Feature 1: FGC-FGC_GSD, Feature 2: FGC-FGC_SRR, Correlation: 1.00
 Feature 1: FGC-FGC_GSD, Feature 2: FGC-FGC_TL, Correlation: 1.00
 Feature 1: FGC-FGC_GSD, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
 Feature 1: FGC-FGC_GSD, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
 Feature 1: FGC-FGC_GSD, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
 Feature 1: FGC-FGC_GSD, Feature 2: PreInt_EduHx-computerinternet_hoursday, Correlation: -1.00
 Feature 1: FGC-FGC_PU, Feature 2: BIA-BIA_BMC, Correlation: 0.99
 Feature 1: FGC-FGC_PU, Feature 2: BIA-BIA_BMR, Correlation: 0.93
 Feature 1: FGC-FGC_PU, Feature 2: BIA-BIA_DEE, Correlation: 1.00
 Feature 1: FGC-FGC_PU, Feature 2: BIA-BIA_ECW, Correlation: 0.85
 Feature 1: FGC-FGC_PU, Feature 2: BIA-BIA_FFM, Correlation: 0.93
 Feature 1: FGC-FGC_PU, Feature 2: BIA-BIA_Frame_num, Correlation: 0.99
 Feature 1: FGC-FGC_PU, Feature 2: BIA-BIA_ICW, Correlation: 0.99
 Feature 1: FGC-FGC_PU, Feature 2: BIA-BIA_LDM, Correlation: 0.98
 Feature 1: FGC-FGC_PU, Feature 2: BIA-BIA_LST, Correlation: 0.93
 Feature 1: FGC-FGC_PU, Feature 2: BIA-BIA_SMM, Correlation: 0.91
 Feature 1: FGC-FGC_PU, Feature 2: BIA-BIA_TBW, Correlation: 0.90
 Feature 1: FGC-FGC_SRL, Feature 2: FGC-FGC_SRL_Zone, Correlation: 0.99
 Feature 1: FGC-FGC_SRL, Feature 2: FGC-FGC_SRR, Correlation: 0.95
 Feature 1: FGC-FGC_SRL, Feature 2: FGC-FGC_SRR_Zone, Correlation: 0.99
 Feature 1: FGC-FGC_SRL, Feature 2: BIA-BIA_BMI, Correlation: 1.00
 Feature 1: FGC-FGC_SRL, Feature 2: BIA-BIA_BMR, Correlation: 0.87
 Feature 1: FGC-FGC_SRL, Feature 2: BIA-BIA_ECW, Correlation: 0.94
 Feature 1: FGC-FGC_SRL, Feature 2: BIA-BIA_FFM, Correlation: 0.87
 Feature 1: FGC-FGC_SRL, Feature 2: BIA-BIA_FFFI, Correlation: 1.00
 Feature 1: FGC-FGC_SRL, Feature 2: BIA-BIA_FMI, Correlation: 0.99
 Feature 1: FGC-FGC_SRL, Feature 2: BIA-BIA_Fat, Correlation: 0.99
 Feature 1: FGC-FGC_SRL, Feature 2: BIA-BIA_LST, Correlation: 0.87
 Feature 1: FGC-FGC_SRL, Feature 2: BIA-BIA_SMM, Correlation: 0.90
 Feature 1: FGC-FGC_SRL, Feature 2: BIA-BIA_TBW, Correlation: 0.90
 Feature 1: FGC-FGC_SRL, Feature 2: SDS-SDS_Total_Raw, Correlation: 0.90
 Feature 1: FGC-FGC_SRL, Feature 2: SDS-SDS_Total_T, Correlation: 0.93
 Feature 1: FGC-FGC_SRL_Zone, Feature 2: FGC-FGC_SRR, Correlation: 0.97
 Feature 1: FGC-FGC_SRL_Zone, Feature 2: FGC-FGC_SRR_Zone, Correlation: 1.00
 Feature 1: FGC-FGC_SRL_Zone, Feature 2: BIA-BIA_BMI, Correlation: 1.00
 Feature 1: FGC-FGC_SRL_Zone, Feature 2: BIA-BIA_BMR, Correlation: 0.87
 Feature 1: FGC-FGC_SRL_Zone, Feature 2: BIA-BIA_ECW, Correlation: 0.94
 Feature 1: FGC-FGC_SRL_Zone, Feature 2: BIA-BIA_FFM, Correlation: 0.87
 Feature 1: FGC-FGC_SRL_Zone, Feature 2: BIA-BIA_FFFI, Correlation: 1.00

Feature 1: FGC-FGC_SRL_Zone, Feature 2: BIA-BIA_FMI, Correlation: 0.99
Feature 1: FGC-FGC_SRL_Zone, Feature 2: BIA-BIA_Fat, Correlation: 0.99
Feature 1: FGC-FGC_SRL_Zone, Feature 2: BIA-BIA_LST, Correlation: 0.87
Feature 1: FGC-FGC_SRL_Zone, Feature 2: BIA-BIA_SMM, Correlation: 0.90
Feature 1: FGC-FGC_SRL_Zone, Feature 2: BIA-BIA_TBW, Correlation: 0.90
Feature 1: FGC-FGC_SRL_Zone, Feature 2: SDS-SDS_Total_Raw, Correlation: 0.95
Feature 1: FGC-FGC_SRL_Zone, Feature 2: SDS-SDS_Total_T, Correlation: 0.97
Feature 1: FGC-FGC_SRR, Feature 2: FGC-FGC_SRR_Zone, Correlation: 0.97
Feature 1: FGC-FGC_SRR, Feature 2: BIA-BIA_BMC, Correlation: 0.84
Feature 1: FGC-FGC_SRR, Feature 2: BIA-BIA_BMI, Correlation: 1.00
Feature 1: FGC-FGC_SRR, Feature 2: BIA-BIA_BMR, Correlation: 0.95
Feature 1: FGC-FGC_SRR, Feature 2: BIA-BIA_ECW, Correlation: 0.99
Feature 1: FGC-FGC_SRR, Feature 2: BIA-BIA_FFM, Correlation: 0.95
Feature 1: FGC-FGC_SRR, Feature 2: BIA-BIA_FFFI, Correlation: 0.99
Feature 1: FGC-FGC_SRR, Feature 2: BIA-BIA_FMI, Correlation: 1.00
Feature 1: FGC-FGC_SRR, Feature 2: BIA-BIA_Fat, Correlation: 1.00
Feature 1: FGC-FGC_SRR, Feature 2: BIA-BIA_ICW, Correlation: 0.84
Feature 1: FGC-FGC_SRR, Feature 2: BIA-BIA_LDM, Correlation: 0.87
Feature 1: FGC-FGC_SRR, Feature 2: BIA-BIA_LST, Correlation: 0.95
Feature 1: FGC-FGC_SRR, Feature 2: BIA-BIA_SMM, Correlation: 0.97
Feature 1: FGC-FGC_SRR, Feature 2: BIA-BIA_TBW, Correlation: 0.97
Feature 1: FGC-FGC_SRR, Feature 2: SDS-SDS_Total_Raw, Correlation: 0.99
Feature 1: FGC-FGC_SRR, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: FGC-FGC_SRR_Zone, Feature 2: BIA-BIA_BMI, Correlation: 1.00
Feature 1: FGC-FGC_SRR_Zone, Feature 2: BIA-BIA_BMR, Correlation: 0.87
Feature 1: FGC-FGC_SRR_Zone, Feature 2: BIA-BIA_ECW, Correlation: 0.94
Feature 1: FGC-FGC_SRR_Zone, Feature 2: BIA-BIA_FFM, Correlation: 0.87
Feature 1: FGC-FGC_SRR_Zone, Feature 2: BIA-BIA_FFFI, Correlation: 1.00
Feature 1: FGC-FGC_SRR_Zone, Feature 2: BIA-BIA_FMI, Correlation: 0.99
Feature 1: FGC-FGC_SRR_Zone, Feature 2: BIA-BIA_Fat, Correlation: 0.99
Feature 1: FGC-FGC_SRR_Zone, Feature 2: BIA-BIA_LST, Correlation: 0.87
Feature 1: FGC-FGC_SRR_Zone, Feature 2: BIA-BIA_SMM, Correlation: 0.90
Feature 1: FGC-FGC_SRR_Zone, Feature 2: BIA-BIA_TBW, Correlation: 0.90
Feature 1: FGC-FGC_SRR_Zone, Feature 2: SDS-SDS_Total_Raw, Correlation: 0.95
Feature 1: FGC-FGC_SRR_Zone, Feature 2: SDS-SDS_Total_T, Correlation: 0.97
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_BMC, Correlation: 0.97
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_BMI, Correlation: 0.91
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_BMR, Correlation: 1.00
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_DEE, Correlation: 0.93
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_ECW, Correlation: 0.98
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_FFM, Correlation: 1.00
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_FFFI, Correlation: 0.90
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_FMI, Correlation: 0.91
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_Fat, Correlation: 0.93
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_Frame_num, Correlation: 0.87
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_ICW, Correlation: 0.97
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_LDM, Correlation: 0.98
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_LST, Correlation: 1.00

Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_SMM, Correlation: 1.00
Feature 1: FGC-FGC_TL, Feature 2: BIA-BIA_TBW, Correlation: 1.00
Feature 1: FGC-FGC_TL, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 0.84
Feature 1: FGC-FGC_TL_Zone, Feature 2: BIA-BIA_BMI, Correlation: -1.00
Feature 1: FGC-FGC_TL_Zone, Feature 2: BIA-BIA_BMR, Correlation: -0.87
Feature 1: FGC-FGC_TL_Zone, Feature 2: BIA-BIA_ECW, Correlation: -0.94
Feature 1: FGC-FGC_TL_Zone, Feature 2: BIA-BIA_FFM, Correlation: -0.87
Feature 1: FGC-FGC_TL_Zone, Feature 2: BIA-BIA_FFFI, Correlation: -1.00
Feature 1: FGC-FGC_TL_Zone, Feature 2: BIA-BIA_FMI, Correlation: -0.99
Feature 1: FGC-FGC_TL_Zone, Feature 2: BIA-BIA_Fat, Correlation: -0.99
Feature 1: FGC-FGC_TL_Zone, Feature 2: BIA-BIA_LST, Correlation: -0.87
Feature 1: FGC-FGC_TL_Zone, Feature 2: BIA-BIA_SMM, Correlation: -0.90
Feature 1: FGC-FGC_TL_Zone, Feature 2: BIA-BIA_TBW, Correlation: -0.90
Feature 1: BIA-BIA_Activity_Level_num, Feature 2: PAQ_C-PAQ_C_Total,
Correlation: -1.00
Feature 1: BIA-BIA_Activity_Level_num, Feature 2: SDS-SDS_Total_Raw,
Correlation: -1.00
Feature 1: BIA-BIA_Activity_Level_num, Feature 2: SDS-SDS_Total_T, Correlation:
-1.00
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_BMR, Correlation: 0.97
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_DEE, Correlation: 0.99
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_ECW, Correlation: 0.91
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_FFM, Correlation: 0.97
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_Fat, Correlation: 0.82
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_Frame_num, Correlation: 0.96
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_ICW, Correlation: 1.00
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_LDM, Correlation: 1.00
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_LST, Correlation: 0.97
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_SMM, Correlation: 0.95
Feature 1: BIA-BIA_BMC, Feature 2: BIA-BIA_TBW, Correlation: 0.95
Feature 1: BIA-BIA_BMC, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_BMC, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_BMC, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: BIA-BIA_BMC, Feature 2: PreInt_EduHx-computerinternet_hoursday,
Correlation: -0.96
Feature 1: BIA-BIA_BMI, Feature 2: BIA-BIA_BMR, Correlation: 0.91
Feature 1: BIA-BIA_BMI, Feature 2: BIA-BIA_ECW, Correlation: 0.97
Feature 1: BIA-BIA_BMI, Feature 2: BIA-BIA_FFM, Correlation: 0.91
Feature 1: BIA-BIA_BMI, Feature 2: BIA-BIA_FFFI, Correlation: 1.00
Feature 1: BIA-BIA_BMI, Feature 2: BIA-BIA_FMI, Correlation: 1.00
Feature 1: BIA-BIA_BMI, Feature 2: BIA-BIA_Fat, Correlation: 1.00
Feature 1: BIA-BIA_BMI, Feature 2: BIA-BIA_LDM, Correlation: 0.82
Feature 1: BIA-BIA_BMI, Feature 2: BIA-BIA_LST, Correlation: 0.91
Feature 1: BIA-BIA_BMI, Feature 2: BIA-BIA_SMM, Correlation: 0.94
Feature 1: BIA-BIA_BMI, Feature 2: BIA-BIA_TBW, Correlation: 0.94
Feature 1: BIA-BIA_BMI, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_BMI, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_BMI, Feature 2: SDS-SDS_Total_T, Correlation: 1.00

Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_DEE, Correlation: 0.92
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_ECW, Correlation: 0.98
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_FFM, Correlation: 1.00
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_FFFMI, Correlation: 0.90
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_FMI, Correlation: 0.91
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_Fat, Correlation: 0.93
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_Frame_num, Correlation: 0.87
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_ICW, Correlation: 0.97
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_LDM, Correlation: 0.98
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_LST, Correlation: 1.00
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_SMM, Correlation: 1.00
Feature 1: BIA-BIA_BMR, Feature 2: BIA-BIA_TBW, Correlation: 1.00
Feature 1: BIA-BIA_BMR, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_BMR, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_BMR, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: BIA-BIA_BMR, Feature 2: PreInt_EduHx-computerinternet_hoursday, Correlation: -0.87
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_ECW, Correlation: 0.84
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_FFM, Correlation: 0.92
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_Frame_num, Correlation: 0.99
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_ICW, Correlation: 0.99
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_LDM, Correlation: 0.98
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_LST, Correlation: 0.92
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_SMM, Correlation: 0.90
Feature 1: BIA-BIA_DEE, Feature 2: BIA-BIA_TBW, Correlation: 0.90
Feature 1: BIA-BIA_DEE, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_DEE, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_DEE, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: BIA-BIA_DEE, Feature 2: PreInt_EduHx-computerinternet_hoursday, Correlation: -0.99
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_FFM, Correlation: 0.98
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_FFFMI, Correlation: 0.97
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_FMI, Correlation: 0.97
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_Fat, Correlation: 0.98
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_ICW, Correlation: 0.91
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_LDM, Correlation: 0.93
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_LST, Correlation: 0.98
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_SMM, Correlation: 0.99
Feature 1: BIA-BIA_ECW, Feature 2: BIA-BIA_TBW, Correlation: 0.99
Feature 1: BIA-BIA_ECW, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_ECW, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_ECW, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_FFFMI, Correlation: 0.90
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_FMI, Correlation: 0.91
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_Fat, Correlation: 0.93
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_Frame_num, Correlation: 0.87
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_ICW, Correlation: 0.97
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_LDM, Correlation: 0.98

Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_LST, Correlation: 1.00
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_SMM, Correlation: 1.00
Feature 1: BIA-BIA_FFM, Feature 2: BIA-BIA_TBW, Correlation: 1.00
Feature 1: BIA-BIA_FFM, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_FFM, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_FFM, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: BIA-BIA_FFM, Feature 2: PreInt_EduHx-computerinternet_hoursday, Correlation: -0.87
Feature 1: BIA-BIA_FFFMI, Feature 2: BIA-BIA_FMI, Correlation: 1.00
Feature 1: BIA-BIA_FFFMI, Feature 2: BIA-BIA_Fat, Correlation: 1.00
Feature 1: BIA-BIA_FFFMI, Feature 2: BIA-BIA_LDM, Correlation: 0.81
Feature 1: BIA-BIA_FFFMI, Feature 2: BIA-BIA_LST, Correlation: 0.91
Feature 1: BIA-BIA_FFFMI, Feature 2: BIA-BIA_SMM, Correlation: 0.93
Feature 1: BIA-BIA_FFFMI, Feature 2: BIA-BIA_TBW, Correlation: 0.93
Feature 1: BIA-BIA_FFFMI, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_FFFMI, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_FFFMI, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: BIA-BIA_FMI, Feature 2: BIA-BIA_Fat, Correlation: 1.00
Feature 1: BIA-BIA_FMI, Feature 2: BIA-BIA_LDM, Correlation: 0.82
Feature 1: BIA-BIA_FMI, Feature 2: BIA-BIA_LST, Correlation: 0.92
Feature 1: BIA-BIA_FMI, Feature 2: BIA-BIA_SMM, Correlation: 0.94
Feature 1: BIA-BIA_FMI, Feature 2: BIA-BIA_TBW, Correlation: 0.94
Feature 1: BIA-BIA_FMI, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_FMI, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_FMI, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: BIA-BIA_Fat, Feature 2: BIA-BIA_ICW, Correlation: 0.82
Feature 1: BIA-BIA_Fat, Feature 2: BIA-BIA_LDM, Correlation: 0.85
Feature 1: BIA-BIA_Fat, Feature 2: BIA-BIA_LST, Correlation: 0.94
Feature 1: BIA-BIA_Fat, Feature 2: BIA-BIA_SMM, Correlation: 0.96
Feature 1: BIA-BIA_Fat, Feature 2: BIA-BIA_TBW, Correlation: 0.96
Feature 1: BIA-BIA_Fat, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_Fat, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_Fat, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: BIA-BIA_Frame_num, Feature 2: BIA-BIA_ICW, Correlation: 0.96
Feature 1: BIA-BIA_Frame_num, Feature 2: BIA-BIA_LDM, Correlation: 0.94
Feature 1: BIA-BIA_Frame_num, Feature 2: BIA-BIA_LST, Correlation: 0.86
Feature 1: BIA-BIA_Frame_num, Feature 2: BIA-BIA_SMM, Correlation: 0.83
Feature 1: BIA-BIA_Frame_num, Feature 2: BIA-BIA_TBW, Correlation: 0.83
Feature 1: BIA-BIA_Frame_num, Feature 2: PreInt_EduHx-computerinternet_hoursday, Correlation: -1.00
Feature 1: BIA-BIA_ICW, Feature 2: BIA-BIA_LDM, Correlation: 1.00
Feature 1: BIA-BIA_ICW, Feature 2: BIA-BIA_LST, Correlation: 0.97
Feature 1: BIA-BIA_ICW, Feature 2: BIA-BIA_SMM, Correlation: 0.95
Feature 1: BIA-BIA_ICW, Feature 2: BIA-BIA_TBW, Correlation: 0.95
Feature 1: BIA-BIA_ICW, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_ICW, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_ICW, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: BIA-BIA_ICW, Feature 2: PreInt_EduHx-computerinternet_hoursday,

```

Correlation: -0.96
Feature 1: BIA-BIA_LDM, Feature 2: BIA-BIA_LST, Correlation: 0.98
Feature 1: BIA-BIA_LDM, Feature 2: BIA-BIA_SMM, Correlation: 0.97
Feature 1: BIA-BIA_LDM, Feature 2: BIA-BIA_TBW, Correlation: 0.97
Feature 1: BIA-BIA_LDM, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_LDM, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_LDM, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: BIA-BIA_LDM, Feature 2: PreInt_EduHx-computerinternet_hoursday,
Correlation: -0.94
Feature 1: BIA-BIA_LST, Feature 2: BIA-BIA_SMM, Correlation: 1.00
Feature 1: BIA-BIA_LST, Feature 2: BIA-BIA_TBW, Correlation: 1.00
Feature 1: BIA-BIA_LST, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_LST, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_LST, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: BIA-BIA_LST, Feature 2: PreInt_EduHx-computerinternet_hoursday,
Correlation: -0.86
Feature 1: BIA-BIA_SMM, Feature 2: BIA-BIA_TBW, Correlation: 1.00
Feature 1: BIA-BIA_SMM, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_SMM, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_SMM, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: BIA-BIA_SMM, Feature 2: PreInt_EduHx-computerinternet_hoursday,
Correlation: -0.83
Feature 1: BIA-BIA_TBW, Feature 2: PAQ_C-PAQ_C_Total, Correlation: 1.00
Feature 1: BIA-BIA_TBW, Feature 2: SDS-SDS_Total_Raw, Correlation: 1.00
Feature 1: BIA-BIA_TBW, Feature 2: SDS-SDS_Total_T, Correlation: 1.00
Feature 1: BIA-BIA_TBW, Feature 2: PreInt_EduHx-computerinternet_hoursday,
Correlation: -0.83
Feature 1: SDS-SDS_Total_Raw, Feature 2: SDS-SDS_Total_T, Correlation: 1.00

```

[65]: test_df.head()

	id	Basic_Demos-Enroll_Season	Basic_Demos-Age	Basic_Demos-Sex	\
0	00008ff9	Fall	5	0	
2	00105258	Summer	10	1	
3	00115b9f	Winter	9	0	
5	001f3379	Spring	13	1	
11	00abe655	Fall	11	0	

	CGAS-Season	CGAS-CGAS_Score	Physical-Season	Physical-BMI	\
0	Winter	51.0	Fall	16.877316	
2	Fall	71.0	Fall	16.648696	
3	Fall	71.0	Summer	18.292347	
5	Winter	50.0	Summer	22.279952	
11	Summer	66.0	NaN	NaN	

	Physical-Height	Physical-Weight	Physical-Waist_Circumference	\
0	46.0	50.8	NaN	

2	56.5	75.6		NaN	
3	56.0	81.6		NaN	
5	59.5	112.2		NaN	
11	NaN	NaN		NaN	
	Physical-Diastolic_BP	Physical-HeartRate	Physical-Systolic_BP	\	
0	NaN	NaN	NaN		
2	65.0	94.0	117.0		
3	60.0	97.0	117.0		
5	60.0	73.0	102.0		
11	NaN	NaN	NaN		
	Fitness_Endurance-Season	Fitness_Endurance-Max_Stage	\		
0	NaN	NaN			
2	Fall	5.0			
3	Summer	6.0			
5	NaN	NaN			
11	NaN	NaN			
	Fitness_Endurance-Time_Mins	Fitness_Endurance-Time_Sec	FGC-Season	\	
0	NaN	NaN	Fall		
2	7.0	33.0	Fall		
3	9.0	37.0	Summer		
5	NaN	NaN	Summer		
11	NaN	NaN	Winter		
	FGC-FGC CU	FGC-FGC CU_Zone	FGC-FGC GSND	FGC-FGC GSND_Zone	FGC-FGC GSD \
0	0.0	0.0	NaN	NaN	NaN
2	20.0	1.0	10.2	1.0	14.7
3	18.0	1.0	NaN	NaN	NaN
5	12.0	0.0	16.5	2.0	17.9
11	NaN	NaN	NaN	NaN	NaN
	FGC-FGC GSD_Zone	FGC-FGC PU	FGC-FGC PU_Zone	FGC-FGC SRL	\
0	NaN	0.0	0.0	7.0	
2	2.0	7.0	1.0	10.0	
3	NaN	5.0	0.0	7.0	
5	2.0	6.0	0.0	10.0	
11	NaN	NaN	NaN	NaN	
	FGC-FGC SRL_Zone	FGC-FGC SRR	FGC-FGC SRR_Zone	FGC-FGC TL	\
0	0.0	6.0	0.0	6.0	
2	1.0	10.0	1.0	5.0	
3	0.0	7.0	0.0	7.0	
5	1.0	11.0	1.0	8.0	
11	NaN	NaN	NaN	NaN	

	FGC-FGC_TL_Zone	BIA-Season	BIA-BIA_Activity_Level_num	BIA-BIA_BMC	\	
0	1.0	Fall	2.0	2.66855		
2	0.0	NaN	NaN	NaN		
3	1.0	Summer	3.0	3.84191		
5	0.0	Summer	2.0	4.33036		
11	NaN	NaN	NaN	NaN		
	BIA-BIA_BMI	BIA-BIA_BMR	BIA-BIA_DEE	BIA-BIA_ECW	BIA-BIA_FFM	\
0	16.8792	932.498	1492.00	8.25598	41.5862	
2	NaN	NaN	NaN	NaN	NaN	
3	18.2943	1131.430	1923.44	15.59250	62.7757	
5	30.1865	1330.970	1996.45	30.21240	84.0285	
11	NaN	NaN	NaN	NaN	NaN	
	BIA-BIA_FFMI	BIA-BIA_FMI	BIA-BIA_Fat	BIA-BIA_Frame_num	BIA-BIA_ICW	\
0	13.8177	3.06143	9.21377	1.0	24.4349	
2	NaN	NaN	NaN	NaN	NaN	
3	14.0740	4.22033	18.82430	2.0	30.4041	
5	16.6877	13.49880	67.97150	2.0	32.9141	
11	NaN	NaN	NaN	NaN	NaN	
	BIA-BIA_LDM	BIA-BIA_LST	BIA-BIA_SMM	BIA-BIA_TBW	PAQ_A-Season	\
0	8.89536	38.9177	19.5413	32.6909	NaN	
2	NaN	NaN	NaN	NaN	NaN	
3	16.77900	58.9338	26.4798	45.9966	NaN	
5	20.90200	79.6982	35.3804	63.1265	NaN	
11	NaN	NaN	NaN	NaN	NaN	
	PAQ_A-PAQ_A_Total	PAQ_C-Season	PAQ_C-PAQ_C_Total	SDS-Season	\	
0	NaN	NaN	NaN	NaN		
2	NaN	Summer	2.170	Fall		
3	NaN	Winter	2.451	Summer		
5	NaN	Spring	4.110	Summer		
11	NaN	Winter	1.100	Winter		
	SDS-SDS_Total_Raw	SDS-SDS_Total_T	PreInt_EduHx-Season	\		
0	NaN	NaN	Fall			
2	38.0	54.0	Summer			
3	31.0	45.0	Winter			
5	40.0	56.0	Spring			
11	42.0	59.0	Fall			
	PreInt_EduHx-computerinternet_hoursday	Age_Group				
0		3.0	NaN			
2		2.0	5-10			
3		0.0	5-10			
5		0.0	11-15			

[66]: test_df.columns

```
[66]: Index(['id', 'Basic_Demos-Enroll_Season', 'Basic_Demos-Age', 'Basic_Demos-Sex',
       'CGAS-Season', 'CGAS-CGAS_Score', 'Physical-Season', 'Physical-BMI',
       'Physical-Height', 'Physical-Weight', 'Physical-Waist_Circumference',
       'Physical-Diastolic_BP', 'Physical-HeartRate', 'Physical-Systolic_BP',
       'Fitness_Endurance-Season', 'Fitness_Endurance-Max_Stage',
       'Fitness_Endurance-Time_Mins', 'Fitness_Endurance-Time_Sec',
       'FGC-Season', 'FGC-FGC_CU', 'FGC-FGC CU_Zone', 'FGC-FGC GSND',
       'FGC-FGC GSND_Zone', 'FGC-FGC_GSD', 'FGC-FGC_GSD_Zone', 'FGC-FGC_PU',
       'FGC-FGC PU_Zone', 'FGC-FGC_SRL', 'FGC-FGC_SRL_Zone', 'FGC-FGC_SRR',
       'FGC-FGC_SRR_Zone', 'FGC-FGC_TL', 'FGC-FGC_TL_Zone', 'BIA-Season',
       'BIA-BIA_Activity_Level_num', 'BIA-BIA_BMC', 'BIA-BIA_BMI',
       'BIA-BIA_BMR', 'BIA-BIA_DEE', 'BIA-BIA_ECW', 'BIA-BIA_FFM',
       'BIA-BIA_FFMI', 'BIA-BIA_FMI', 'BIA-BIA_Fat', 'BIA-BIA_Frame_num',
       'BIA-BIA_ICW', 'BIA-BIA_LDM', 'BIA-BIA_LST', 'BIA-BIA_SMM',
       'BIA-BIA_TBW', 'PAQ_A-Season', 'PAQ_A-PAQ_A_Total', 'PAQ_C-Season',
       'PAQ_C-PAQ_C_Total', 'SDS-Season', 'SDS-SDS_Total_Raw',
       'SDS-SDS_Total_T', 'PreInt_EduHx-Season',
       'PreInt_EduHx-computerinternet_hoursday', 'Age_Group'],
      dtype='object')
```

```
[67]: # Step 1: Import necessary libraries
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
import category_encoders as ce # for target encoding if needed
import numpy as np
import pandas as pd

# Step 2: Handle Missing Values in Numeric Columns
# Select numeric columns in test_df for imputation
numeric_features_test = test_df.select_dtypes(include=[np.number]).columns

# Remove columns with only missing values
non_missing_numeric_features_test = [col for col in numeric_features_test if
    ~test_df[col].notnull().any()]

# Use IterativeImputer to perform MICE imputation on numeric columns in test_df
mice_imputer_test = IterativeImputer(max_iter=10, random_state=42)
imputed_values_test = mice_imputer_test.
    ↪fit_transform(test_df[non_missing_numeric_features_test])

# Replace original DataFrame's numeric columns (that have non-missing values) with MICE-imputed values
test_df[non_missing_numeric_features_test] = imputed_values_test
```

```

# Step 3: Handle Missing Values in Categorical Features
# Select categorical features in test_df
categorical_features_test = test_df.select_dtypes(include=['category', u
↪'object']).columns

# Check if categorical features exist in test_df
if len(categorical_features_test) > 0:
    print(f"Categorical features identified in test_df: {categorical_features_test}")

    # Apply simple mode imputation for categorical columns (as we don't have a target variable for encoding)
    test_df[categorical_features_test] = test_df[categorical_features_test].fillna(test_df[categorical_features_test].mode().iloc[0])
else:
    print("No categorical features found for encoding in test_df.")

# Step 4: Create Missingness Indicator Columns
# Define threshold for missingness indicator creation (10% missingness)
missing_threshold_test = 0.1

# Create missingness indicator columns
for col in test_df.columns:
    missing_ratio_test = test_df[col].isnull().mean()
    if missing_ratio_test >= missing_threshold_test:
        # Create missingness indicator
        missing_indicator_col_test = f"{col}_missing"
        test_df[missing_indicator_col_test] = test_df[col].isnull().astype(int)
        print(f"Created missingness indicator for {col} in test_df (Missing Ratio: {missing_ratio_test:.2f})")

# Final output: Print remaining columns and missing values status
print(f"Remaining columns after missing value handling in test_df: {test_df.columns}")
print("\nRemaining missing values in test_df after imputation:")
print(test_df.isnull().sum())

```

Categorical features identified in test_df: Index(['id', 'Basic_Demos-Enroll_Season', 'CGAS-Season', 'Physical-Season', 'Fitness_Endurance-Season', 'FGC-Season', 'BIA-Season', 'PAQ_A-Season', 'PAQ_C-Season', 'SDS-Season', 'PreInt_EduHx-Season', 'Age_Group'],
dtype='object')

Created missingness indicator for Physical-Waist_Circumference in test_df (Missing Ratio: 1.00)

Created missingness indicator for PAQ_A-Season in test_df (Missing Ratio: 1.00)

Created missingness indicator for PAQ_A-PAQ_A_Total in test_df (Missing Ratio:

```

1.00)
Remaining columns after missing value handling in test_df: Index(['id',
'Basic_Demos-Enroll_Season', 'Basic_Demos-Age', 'Basic_Demos-Sex',
'CGAS-Season', 'CGAS-CGAS_Score', 'Physical-Season', 'Physical-BMI',
'Physical-Height', 'Physical-Weight', 'Physical-Waist_Circumference',
'Physical-Diastolic_BP', 'Physical-HeartRate', 'Physical-Systolic_BP',
'Fitness_Endurance-Season', 'Fitness_Endurance-Max_Stage',
'Fitness_Endurance-Time_Mins', 'Fitness_Endurance-Time_Sec',
'FGC-Season', 'FGC-FGC CU', 'FGC-FGC CU_Zone', 'FGC-FGC GSND',
'FGC-FGC GSND_Zone', 'FGC-FGC_GSD', 'FGC-FGC_GSD_Zone', 'FGC-FGC_PU',
'FGC-FGC_PU_Zone', 'FGC-FGC_SRL', 'FGC-FGC_SRL_Zone', 'FGC-FGC_SRR',
'FGC-FGC_SRR_Zone', 'FGC-FGC_TL', 'FGC-FGC_TL_Zone', 'BIA-Season',
'BIA-BIA_Activity_Level_num', 'BIA-BIA_BMC', 'BIA-BIA_BMI',
'BIA-BIA_BMR', 'BIA-BIA_DEE', 'BIA-BIA_ECW', 'BIA-BIA_FFM',
'BIA-BIA_FFM', 'BIA-BIA_FMI', 'BIA-BIA_Fat', 'BIA-BIA_Frame_num',
'BIA-BIA_ICW', 'BIA-BIA_LDM', 'BIA-BIA_LST', 'BIA-BIA_SMM',
'BIA-BIA_TBW', 'PAQ_A-Season', 'PAQ_A-PAQ_A_Total', 'PAQ_C-Season',
'PAQ_C-PAQ_C_Total', 'SDS-Season', 'SDS-SDS_Total_Raw',
'SDS-SDS_Total_T', 'PreInt_EduHx-Season',
'PreInt_EduHx-computerinternet_hoursday', 'Age_Group',
'Physical-Waist_Circumference_missing', 'PAQ_A-Season_missing',
'PAQ_A-PAQ_A_Total_missing'],
dtype='object')

Remaining missing values in test_df after imputation:
id                      0
Basic_Demos-Enroll_Season      0
Basic_Demos-Age                  0
Basic_Demos-Sex                  0
CGAS-Season                      0
                               ..
PreInt_EduHx-computerinternet_hoursday 0
Age_Group                         0
Physical-Waist_Circumference_missing 0
PAQ_A-Season_missing                0
PAQ_A-PAQ_A_Total_missing          0
Length: 63, dtype: int64

/opt/conda/lib/python3.10/site-packages/sklearn/impute/_iterative.py:825:
ConvergenceWarning: [IterativeImputer] Early stopping criterion not reached.
    warnings.warn(
/var/tmp/ipykernel_7796/2051824373.py:31: FutureWarning: Downcasting object
dtype arrays on .fillna, .ffill, .bfill is deprecated and will change in a
future version. Call result.infer_objects(copy=False) instead. To opt-in to the
future behavior, set `pd.set_option('future.no_silent_downcasting', True)`  

    test_df[categorical_features_test] = test_df[categorical_features_test].fillna
(test_df[categorical_features_test].mode().iloc[0])

```

```
[68]: test_df.head()
```

```
[68]:      id Basic_Demos-Enroll_Season  Basic_Demos-Age  Basic_Demos-Sex \
0    00008ff9                      Fall            5.0          0.0
2    00105258                     Summer          10.0          1.0
3    00115b9f                     Winter          9.0          0.0
5    001f3379                     Spring          13.0          1.0
11   00abe655                     Fall           11.0          0.0

      CGAS-Season  CGAS-CGAS_Score  Physical-Season  Physical-BMI \
0        Winter          51.0          Fall       16.877316
2        Fall           71.0          Fall       16.648696
3        Fall           71.0        Summer      18.292347
5        Winter          50.0        Summer      22.279952
11       Summer          66.0          Fall       17.864055

      Physical-Height  Physical-Weight  Physical-Waist_Circumference \
0        46.000000     50.800000                  NaN
2        56.500000     75.600000                  NaN
3        56.000000     81.600000                  NaN
5        59.500000    112.200000                  NaN
11       53.089389     73.360103                  NaN

      Physical-Diastolic_BP  Physical-HeartRate  Physical-Systolic_BP \
0          76.659994      42.625084       95.537106
2          65.000000      94.000000      117.000000
3          60.000000      97.000000      117.000000
5          60.000000      73.000000      102.000000
11         64.906547      79.417997      109.671015

      Fitness_Endurance-Season  Fitness_Endurance-Max_Stage \
0                      Fall           0.108192
2                      Fall           5.000000
3                    Summer           6.000000
5                      Fall           8.161510
11                     Fall           4.434398

      Fitness_Endurance-Time_Mins  Fitness_Endurance-Time_Sec FGC-Season \
0             -2.783656          13.432611      Fall
2              7.000000          33.000000      Fall
3              9.000000          37.000000  Summer
5             13.323058          45.646307  Summer
11            5.868766          30.737339  Winter

      FGC-FGC CU  FGC-FGC CU_Zone  FGC-FGC GSND  FGC-FGC GSND_Zone  FGC-FGC GSD \
0        0.000000          0.000000      3.706899        -0.030646      11.401920
2        20.000000         1.000000     10.200000         1.000000     14.700000
```

3	18.000000	1.000000	11.694644	1.237246	15.459184	
5	12.000000	0.000000	16.500000	2.000000	17.900000	
11	11.771994	0.48317	9.702796	0.921081	14.447450	
	FGC-FGC_GSD_Zone	FGC-FGC_PU	FGC-FGC_PU_Zone	FGC-FGC_SRL	\	
0	2.0	0.000000	0.000000	7.000000		
2	2.0	7.000000	1.000000	10.000000		
3	2.0	5.000000	0.000000	7.000000		
5	2.0	6.000000	0.000000	10.000000		
11	2.0	4.413705	0.458711	9.593142		
	FGC-FGC_SRL_Zone	FGC-FGC_SRR	FGC-FGC_SRR_Zone	FGC-FGC_TL	\	
0	0.000000	6.000000	0.000000	6.00000		
2	1.000000	10.000000	1.000000	5.00000		
3	0.000000	7.000000	0.000000	7.00000		
5	1.000000	11.000000	1.000000	8.00000		
11	0.832517	9.539816	0.834634	6.11333		
	FGC-FGC_TL_Zone	BIA-Season	BIA-BIA_Activity_Level_num	BIA-BIA_BMC	\	
0	1.000000	Fall	2.000000	2.668550		
2	0.000000	Summer	2.940449	3.641048		
3	1.000000	Summer	3.000000	3.841910		
5	0.000000	Summer	2.000000	4.330360		
11	0.357534	Summer	2.634960	3.539088		
	BIA-BIA_BMI	BIA-BIA_BMR	BIA-BIA_DEE	BIA-BIA_ECW	BIA-BIA_FFM	\
0	16.879200	932.498000	1492.000000	8.255980	41.586200	
2	17.160848	1087.854533	1858.417991	13.394408	58.139277	
3	18.294300	1131.430000	1923.440000	15.592500	62.775700	
5	30.186500	1330.970000	1996.450000	30.212400	84.028500	
11	18.782182	1087.500178	1803.297738	14.468455	58.086989	
	BIA-BIA_FFMI	BIA-BIA_FMI	BIA-BIA_Fat	BIA-BIA_Frame_num	BIA-BIA_ICW	\
0	13.817700	3.061430	9.213770	1.000000	24.434900	
2	13.825440	3.303771	13.482399	1.863178	29.381756	
3	14.074000	4.220330	18.824300	2.000000	30.404100	
5	16.687700	13.498800	67.971500	2.000000	32.914100	
11	14.178944	4.520419	19.377546	1.710098	28.844178	
	BIA-BIA_LDM	BIA-BIA_LST	BIA-BIA_SMM	BIA-BIA_TBW	PAQ_A-Season	\
0	8.895360	38.917700	19.541300	32.690900	NaN	
2	15.362565	54.493534	24.801015	42.771962	NaN	
3	16.779000	58.933800	26.479800	45.996600	NaN	
5	20.902000	79.698200	35.380400	63.126500	NaN	
11	14.773667	54.540391	25.072255	43.300657	NaN	
	PAQ_A-PAQ_A_Total	PAQ_C-Season	PAQ_C-PAQ_C_Total	SDS-Season	\	

0	NaN	Winter	-2.892886	Summer
2	NaN	Summer	2.170000	Fall
3	NaN	Winter	2.451000	Summer
5	NaN	Spring	4.110000	Summer
11	NaN	Winter	1.100000	Winter
	SDS-SDS_Total_Raw	SDS-SDS_Total_T	PreInt_EduHx-Season	\
0	65.892149	89.323116		Fall
2	38.000000	54.000000		Summer
3	31.000000	45.000000		Winter
5	40.000000	56.000000		Spring
11	42.000000	59.000000		Fall
	PreInt_EduHx-computerinternet_hoursday	Age_Group	\	
0		3.0	5-10	
2		2.0	5-10	
3		0.0	5-10	
5		0.0	11-15	
11		0.0	11-15	
	Physical-Waist_Circumference_missing	PAQ_A-Season_missing	\	
0		1	1	
2		1	1	
3		1	1	
5		1	1	
11		1	1	
	PAQ_A-PAQ_A_Total_missing			
0		1		
2		1		
3		1		
5		1		
11		1		

```
[69]: # Aggregate actigraphy data by ID
actigraphy_test_summary_df = (
    actigraphy_test_df
    .groupby('ID') # Group by ID
    .agg({
        'X': ['mean', 'std', 'min', 'max'], # Aggregate X with mean, std, min, max
        'Y': ['mean', 'std', 'min', 'max'], # Aggregate Y with mean, std, min, max
        'Z': ['mean', 'std', 'min', 'max'], # Aggregate Z with mean, std, min, max
        'enmo': ['mean', 'std'], # Aggregate enmo with mean, std
        'anglez': ['mean', 'std'], # Aggregate anglez with mean, std
    })
)
```

```

        'non-wear_flag': 'mean', # Proportion of non-wear time
        'light': ['mean', 'std'], # Aggregate light with mean, std
        'battery_voltage': ['mean', 'std'], # Aggregate battery voltage
        'time_of_day': 'mean', # Mean time of day
        'weekday': 'mean', # Average weekday for the activity readings
        'quarter': 'mean', # Average quarter for the activity readings
        'relative_date_PCIAT': 'mean' # Average relative date PCIAT
    })
)

# Flatten MultiIndex columns
actigraphy_test_summary_df.columns = ['_'.join(col) for col in
                                       actigraphy_test_summary_df.columns]

# Reset index to make 'ID' a column again
actigraphy_test_summary_df.reset_index(inplace=True)

# Display first few rows of the aggregated summary
actigraphy_test_summary_df.head()

```

[69]:

	ID	X_mean	X_std	X_min	X_max	Y_mean	Y_std	\
0	00115b9f	-0.316384	0.453665	-1.746094	1.507865	0.016009	0.502702	
1	001f3379	-0.004272	0.351545	-1.038711	1.034351	0.016859	0.303812	
	Y_min	Y_max	Z_mean	Z_std	Z_min	Z_max	enmo_mean	\
0	-2.905339	1.666354	-0.167890	0.585710	-1.048372	1.546979	0.047388	
1	-1.522690	1.946303	-0.631731	0.623476	-1.018787	1.146284	0.011926	
	enmo_std	anglez_mean	anglez_std	non-wear_flag_mean	light_mean	\		
0	0.106351	-10.580416	42.947170		0.000000	42.29631		
1	0.024331	-55.630768	50.303635		0.655708	16.77198		
	light_std	battery_voltage_mean	battery_voltage_std	time_of_day_mean	\			
0	208.168976		4053.578857	112.404037	5.046215e+13			
1	95.327438		3838.189453	155.573868	4.321212e+13			
	weekday_mean	quarter_mean	relative_date_PCIAT_mean					
0	4.470182	3.0		53.201683				
1	3.909848	3.0		79.435593				

[70]:

```

import numpy as np

# Function to compute top n Fourier coefficients
def compute_top_n_fourier_coefficients(signal, n=5):
    # Perform the Fourier Transform on the signal
    fft_coeffs = np.fft.fft(signal)
    # Calculate magnitudes of the FFT coefficients

```

```

    magnitudes = np.abs(fft_coeffs)
    # Get top n coefficients based on magnitudes (excluding the DC component at index 0)
    top_n_indices = np.argsort(magnitudes)[-n:]
    # Return the real and imaginary parts of the top n coefficients
    top_n_real_parts = fft_coeffs[top_n_indices].real
    top_n_imag_parts = fft_coeffs[top_n_indices].imag
    return top_n_real_parts, top_n_imag_parts

# List to store Fourier features for each participant
fourier_features_list = []

# Calculate Fourier Transforms for each ID in the actigraphy training data
for participant_id, participant_data in actigraphy_test_df.groupby('ID'):
    # Calculate Fourier coefficients for each axis
    fourier_X_real, fourier_X_imag = compute_top_n_fourier_coefficients(participant_data['X'].values)
    fourier_Y_real, fourier_Y_imag = compute_top_n_fourier_coefficients(participant_data['Y'].values)
    fourier_Z_real, fourier_Z_imag = compute_top_n_fourier_coefficients(participant_data['Z'].values)

    # Create a dictionary to store Fourier features for this participant
    fourier_features = {
        'ID': participant_id,
        'fourier_X_real': fourier_X_real.mean(), # Using mean of the top real parts as a feature
        'fourier_X_imag': fourier_X_imag.mean(), # Using mean of the top imaginary parts as a feature
        'fourier_Y_real': fourier_Y_real.mean(),
        'fourier_Y_imag': fourier_Y_imag.mean(),
        'fourier_Z_real': fourier_Z_real.mean(),
        'fourier_Z_imag': fourier_Z_imag.mean(),
    }
    fourier_features_list.append(fourier_features)

# Convert the list of Fourier features into a DataFrame
fourier_features_df = pd.DataFrame(fourier_features_list)

# Merge the Fourier features into the existing actigraphy summary dataframe
actigraphy_test_summary_with_fourier_df = pd.merge(
    actigraphy_test_summary_df,
    fourier_features_df,
    on='ID',
    how='left'
)

```

```
# Display first few rows of the combined summary
actigraphy_train_summary_with_fourier_df.head()
```

```
[70]:      ID    X_mean     X_std     X_min     X_max    Y_mean     Y_std  \
0  00115b9f -0.316384  0.453665 -1.746094  1.507865  0.016009  0.502702
1  001f3379 -0.004272  0.351545 -1.038711  1.034351  0.016859  0.303812
2  00f332d1  0.208036  0.486977 -1.952594  1.666465  0.057094  0.443755
3  01085eb3 -0.343396  0.516126 -2.284304  1.000692 -0.055826  0.424303
4  012cadd8  0.018670  0.595251 -2.143912  3.341210  0.071660  0.508311

      Y_min     Y_max     Z_mean     Z_std     Z_min     Z_max  enmo_mean  \
0 -2.905339  1.666354 -0.167890  0.585710 -1.048372  1.546979  0.047388
1 -1.522690  1.946303 -0.631731  0.623476 -1.018787  1.146284  0.011926
2 -2.361866  1.016429  0.141550  0.683114 -1.016758  2.239939  0.030255
3 -2.276082  1.011419 -0.254433  0.564593 -1.022549  1.299293  0.032946
4 -3.373025  4.442658 -0.061682  0.578022 -1.003249  2.321265  0.058280

  enmo_std  anglez_mean  anglez_std  non-wear_flag_mean  light_mean  \
0  0.106351   -10.580416  42.947170           0.000000  42.296310
1  0.024331   -55.630768  50.303635           0.655708  16.771980
2  0.104136    6.687339  52.754208           0.171246  66.563393
3  0.083798   -17.589037  39.895645           0.035210  17.800735
4  0.197285   -5.059758  39.994808           0.000000  54.893402

  light_std  battery_voltage_mean  battery_voltage_std  time_of_day_mean  \
0  208.168976                 4053.578857          112.404037  5.046215e+13
1   95.327438                 3838.189453          155.573868  4.321212e+13
2  286.916595                 3848.583252          166.968582  4.318680e+13
3   73.023468                 3849.650146          171.100159  4.338433e+13
4  230.972397                 3974.910889          119.525154  4.343573e+13

  weekday_mean  quarter_mean  relative_date_PCIAT_mean  fourier_X_real  \
0      4.470182            3.0                  53.201683 -2653.531675
1      3.909848            3.0                  79.435593  4103.865122
2      3.832677            2.0                  26.152903  14903.301506
3      3.963284            4.0                  49.910686 -25796.646158
4      4.168412            4.0                 -1.168288  6637.890207

  fourier_X_imag  fourier_Y_real  fourier_Y_imag  fourier_Z_real  \
0   -1.083578e-14       705.803060  -2.074467e+02     1995.401835
1   -1.680035e+03      14385.071425   3.120931e+03  -26765.674436
2   -3.637979e-13      -923.242685   7.275958e-13  -5261.764351
3   -1.093525e-12     -10776.376135  -1.989520e-13  -8614.531458
4    5.618541e+02      2279.335449  -3.637979e-13  -4597.967535

  fourier_Z_imag
```

```

0   -5.684342e-15
1   -8.731149e-12
2    7.275958e-13
3   -9.563905e-13
4    0.000000e+00

```

```
[71]: # Function to calculate day and night activity based on time_of_day
def calculate_day_night_activity(df, day_start=6, day_end=18):
    # Calculate day activity (time_of_day between day_start and day_end)
    day_activity = df[(df['time_of_day'] >= day_start) & (df['time_of_day'] <=
    ↪day_end)]['enmo'].sum()
    # Calculate night activity (time_of_day outside the day range)
    night_activity = df[(df['time_of_day'] < day_start) | (df['time_of_day'] >=
    ↪day_end)]['enmo'].sum()
    return day_activity, night_activity

# List to store time-domain features for each participant
time_features_list = []

# Calculate time-domain features for each participant
for participant_id, participant_data in actigraphy_test_df.groupby('ID'):
    # Calculate day and night activity
    day_activity, night_activity =
    ↪calculate_day_night_activity(participant_data)
    activity_ratio_day_night = day_activity / (night_activity + 1e-6) # Avoid
    ↪division by zero

    # Calculate proportion of non-wear time
    non_wear_proportion = participant_data['non-wear_flag'].mean()

    # Calculate proportion of time spent in different activity levels based on
    ↪'enmo'
    sedentary_time = participant_data[participant_data['enmo'] < 0.05].shape[0]
    light_activity_time = participant_data[(participant_data['enmo'] >= 0.05) &
    ↪(participant_data['enmo'] < 0.5)].shape[0]
    moderate_activity_time = participant_data[(participant_data['enmo'] >= 0.5) &
    ↪(participant_data['enmo'] < 1)].shape[0]
    vigorous_activity_time = participant_data[participant_data['enmo'] >= 1].
    ↪shape[0]
    total_time = participant_data.shape[0]

    # Calculate proportions
    sedentary_proportion = sedentary_time / total_time
    light_activity_proportion = light_activity_time / total_time
    moderate_activity_proportion = moderate_activity_time / total_time
    vigorous_activity_proportion = vigorous_activity_time / total_time
```

```

# Create a dictionary of time domain features
time_features = {
    'ID': participant_id,
    'activity_during_day': day_activity,
    'activity_during_night': night_activity,
    'activity_ratio_day_night': activity_ratio_day_night,
    'non_wear_proportion': non_wear_proportion,
    'sedentary_proportion': sedentary_proportion,
    'light_activity_proportion': light_activity_proportion,
    'moderate_activity_proportion': moderate_activity_proportion,
    'vigorous_activity_proportion': vigorous_activity_proportion
}
time_features_list.append(time_features)

# Convert the list of time domain features into a DataFrame
time_features_df = pd.DataFrame(time_features_list)

# Merge the time-domain features into the actigraphy summary with Fourier
# features
actigraphy_combined_features_test_df = pd.merge(
    actigraphy_test_summary_with_fourier_df, # The dataframe with Fourier
# features
    time_features_df, # The new time-domain features
    on='ID',
    how='left'
)

# Display the first few rows of the final combined feature set
actigraphy_combined_features_test_df.head(10)

```

```

[71]:      ID      X_mean      X_std      X_min      X_max      Y_mean      Y_std  \
0  00115b9f -0.316384  0.453665 -1.746094  1.507865  0.016009  0.502702
1  001f3379 -0.004272  0.351545 -1.038711  1.034351  0.016859  0.303812

      Y_min      Y_max      Z_mean      Z_std      Z_min      Z_max  enmo_mean  \
0 -2.905339  1.666354 -0.167890  0.585710 -1.048372  1.546979  0.047388
1 -1.522690  1.946303 -0.631731  0.623476 -1.018787  1.146284  0.011926

  enmo_std  anglez_mean  anglez_std  non-wear_flag_mean  light_mean  \
0  0.106351   -10.580416   42.947170           0.000000  42.29631
1  0.024331   -55.630768   50.303635           0.655708  16.77198

  light_std  battery_voltage_mean  battery_voltage_std  time_of_day_mean  \
0  208.168976                  4053.578857          112.404037  5.046215e+13
1   95.327438                  3838.189453          155.573868  4.321212e+13

```

```

weekday_mean   quarter_mean   relative_date_PCIAT_mean   fourier_X_real   \
0      4.470182           3.0                  53.201683    -2653.531675
1      3.909848           3.0                  79.435593     4103.865122

fourier_X_imag   fourier_Y_real   fourier_Y_imag   fourier_Z_real   \
0     -1.083578e-14      705.803060     -207.446683     1995.401835
1     -1.680035e+03     14385.071425     3120.930726    -26765.674436

fourier_Z_imag   activity_during_day   activity_during_night   \
0     -5.684342e-15          0.0            2053.305176
1     -8.731149e-12          0.0            4727.518555

activity_ratio_day_night   non_wear_proportion   sedentary_proportion   \
0                  0.0            0.000000        0.792453
1                  0.0            0.655708        0.978501

light_activity_proportion   moderate_activity_proportion   \
0                  0.198131        0.007870
1                  0.021171        0.000288

vigorous_activity_proportion
0                  0.001546
1                  0.000040

```

[72]: # Merging the main training dataset with actigraphy_combined_features_df based on the ID column

```

merged_test_df = pd.merge(test_df, actigraphy_combined_features_test_df, how='left', left_on='id', right_on='ID')

# Dropping the redundant ID column from actigraphy_combined_features_df if needed
merged_test_df = merged_test_df.drop(columns=['ID'])

# Display the first few rows of the merged DataFrame to confirm the merge
#print(merged_train_df.head())

```

[73]: # Define the list of actigraphy feature columns

```

actigraphy_columns = [
    'X_mean', 'X_std', 'X_min', 'X_max', 'Y_mean', 'Y_std', 'Y_min', 'Y_max',
    'Z_mean', 'Z_std', 'Z_min', 'Z_max', 'enmo_mean', 'enmo_std', 'anglez_mean',
    'anglez_std', 'non-wear_flag_mean', 'light_mean', 'light_std',
    'battery_voltage_mean',
    'battery_voltage_std', 'time_of_day_mean', 'weekday_mean', 'quarter_mean',
    'relative_date_PCIAT_mean', 'fourier_X_real', 'fourier_X_imag',
    'fourier_Y_real',
    'fourier_Y_imag', 'fourier_Z_real', 'fourier_Z_imag', 'activity_during_day',
    'activity_during_night', 'activity_ratio_day_night', 'non_wear_proportion',
]

```

```

'sedentary_proportion', 'light_activity_proportion',
↳'moderate_activity_proportion',
'veigorously_activity_proportion'
]

# Fill NaN values in actigraphy columns with zeros if all actigraphy columns
↳are NaN in a row
merged_test_df[actigraphy_columns] = merged_test_df[actigraphy_columns].
↳apply(lambda row: row.fillna(0) if row.isnull().all() else row, axis=1)

# Create actigraphy_present column
# If all actigraphy columns have 0 values for a given row, set
↳actigraphy_present to 0, otherwise 1
merged_test_df['actigraphy_present'] = merged_test_df[actigraphy_columns].
↳apply(lambda row: 0 if (row == 0).all() else 1, axis=1)

# Display the first few rows to verify the results
merged_test_df.head()

```

```
[73]:      id Basic_Demos-Enroll_Season  Basic_Demos-Age  Basic_Demos-Sex \
0  00008ff9                  Fall          5.0          0.0
1  00105258                 Summer         10.0         1.0
2  00115b9f                 Winter          9.0          0.0
3  001f3379                 Spring         13.0         1.0
4  00abe655                  Fall          11.0          0.0

      CGAS-Season  CGAS-CGAS_Score Physical-Season  Physical-BMI  Physical-Height \
0       Winter        51.0          Fall       16.877316     46.000000
1       Fall         71.0          Fall       16.648696     56.500000
2       Fall         71.0         Summer      18.292347     56.000000
3       Winter        50.0         Summer      22.279952     59.500000
4       Summer        66.0          Fall       17.864055     53.089389

      Physical-Weight  Physical-Waist_Circumference  Physical-Diastolic_BP \
0           50.800000                      NaN            76.659994
1           75.600000                      NaN            65.000000
2           81.600000                      NaN            60.000000
3          112.200000                      NaN            60.000000
4           73.360103                      NaN            64.906547

      Physical-HeartRate  Physical-Systolic_BP Fitness_Endurance-Season \
0             42.625084          95.537106                  Fall
1            94.000000          117.000000                  Fall
2            97.000000          117.000000                Summer
3            73.000000          102.000000                  Fall
4            79.417997          109.671015                  Fall

```

	Fitness_Endurance-Max_Stage	Fitness_Endurance-Time_Mins	\			
0	0.108192	-2.783656				
1	5.000000	7.000000				
2	6.000000	9.000000				
3	8.161510	13.323058				
4	4.434398	5.868766				
	Fitness_Endurance-Time_Sec	FGC-Season	FGC-FGC_CU	FGC-FGC_CU_Zone	\	
0	13.432611	Fall	0.000000	0.000000		
1	33.000000	Fall	20.000000	1.000000		
2	37.000000	Summer	18.000000	1.000000		
3	45.646307	Summer	12.000000	0.000000		
4	30.737339	Winter	11.771994	0.48317		
	FGC-FGC_GSND	FGC-FGC_GSND_Zone	FGC-FGC_GSD	FGC-FGC_GSD_Zone	FGC-FGC_PU	\
0	3.706899	-0.030646	11.401920	2.0	0.000000	
1	10.200000	1.000000	14.700000	2.0	7.000000	
2	11.694644	1.237246	15.459184	2.0	5.000000	
3	16.500000	2.000000	17.900000	2.0	6.000000	
4	9.702796	0.921081	14.447450	2.0	4.413705	
	FGC-FGC_PU_Zone	FGC-FGC_SRL	FGC-FGC_SRL_Zone	FGC-FGC_SRR	\	
0	0.000000	7.000000	0.000000	6.000000		
1	1.000000	10.000000	1.000000	10.000000		
2	0.000000	7.000000	0.000000	7.000000		
3	0.000000	10.000000	1.000000	11.000000		
4	0.458711	9.593142	0.832517	9.539816		
	FGC-FGC_SRR_Zone	FGC-FGC_TL	FGC-FGC_TL_Zone	BIA-Season	\	
0	0.000000	6.00000	1.000000	Fall		
1	1.000000	5.00000	0.000000	Summer		
2	0.000000	7.00000	1.000000	Summer		
3	1.000000	8.00000	0.000000	Summer		
4	0.834634	6.11333	0.357534	Summer		
	BIA-BIA_Activity_Level_num	BIA-BIA_BMC	BIA-BIA_BMI	BIA-BIA_BMR	\	
0	2.000000	2.668550	16.879200	932.498000		
1	2.940449	3.641048	17.160848	1087.854533		
2	3.000000	3.841910	18.294300	1131.430000		
3	2.000000	4.330360	30.186500	1330.970000		
4	2.634960	3.539088	18.782182	1087.500178		
	BIA-BIA_DEE	BIA-BIA_ECW	BIA-BIA_FFM	BIA-BIA_FFMI	BIA-BIA_FMI	\
0	1492.000000	8.255980	41.586200	13.817700	3.061430	
1	1858.417991	13.394408	58.139277	13.825440	3.303771	
2	1923.440000	15.592500	62.775700	14.074000	4.220330	
3	1996.450000	30.212400	84.028500	16.687700	13.498800	

4	1803.297738	14.468455	58.086989	14.178944	4.520419			
0	BIA-BIA_Fat	BIA-BIA_Frame_num	BIA-BIA_ICW	BIA-BIA_LDM	BIA-BIA_LST	\		
1	9.213770	1.000000	24.434900	8.895360	38.917700			
2	13.482399	1.863178	29.381756	15.362565	54.493534			
3	18.824300	2.000000	30.404100	16.779000	58.933800			
4	67.971500	2.000000	32.914100	20.902000	79.698200			
5	19.377546	1.710098	28.844178	14.773667	54.540391			
0	BIA-BIA_SMM	BIA-BIA_TBW	PAQ_A-Season	PAQ_A-PAQ_A_Total	PAQ_C-Season	\		
1	19.541300	32.690900	NaN	NaN	Winter			
2	24.801015	42.771962	NaN	NaN	Summer			
3	26.479800	45.996600	NaN	NaN	Winter			
4	35.380400	63.126500	NaN	NaN	Spring			
5	25.072255	43.300657	NaN	NaN	Winter			
0	PAQ_C-PAQ_C_Total	SDS-Season	SDS-SDS_Total_Raw	SDS-SDS_Total_T		\		
1	-2.892886	Summer	65.892149	89.323116				
2	2.170000	Fall	38.000000	54.000000				
3	2.451000	Summer	31.000000	45.000000				
4	4.110000	Summer	40.000000	56.000000				
5	1.100000	Winter	42.000000	59.000000				
0	PreInt_EduHx-Season	PreInt_EduHx-computerinternet_hoursday	Age_Group			\		
1	Fall		3.0	5-10				
2	Summer		2.0	5-10				
3	Winter		0.0	5-10				
4	Spring		0.0	11-15				
5	Fall		0.0	11-15				
0	Physical-Waist_Circumference_missing	PAQ_A-Season_missing				\		
1	1	1						
2	1	1						
3	1	1						
4	1	1						
0	PAQ_A-PAQ_A_Total_missing	X_mean	X_std	X_min	X_max	\		
1	1	0.000000	0.000000	0.000000	0.000000			
2	1	0.000000	0.000000	0.000000	0.000000			
3	1	-0.316384	0.453665	-1.746094	1.507865			
4	1	-0.004272	0.351545	-1.038711	1.034351			
5	1	0.000000	0.000000	0.000000	0.000000			
0	Y_mean	Y_std	Y_min	Y_max	Z_mean	Z_std	Z_min	\
1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	

2	0.016009	0.502702	-2.905339	1.666354	-0.167890	0.585710	-1.048372
3	0.016859	0.303812	-1.522690	1.946303	-0.631731	0.623476	-1.018787
4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	Z_max	enmo_mean	enmo_std	anglez_mean	anglez_std	non-wear_flag_mean	\
0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	1.546979	0.047388	0.106351	-10.580416	42.947170		0.000000
3	1.146284	0.011926	0.024331	-55.630768	50.303635		0.655708
4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	light_mean	light_std	battery_voltage_mean	battery_voltage_std	\		
0	0.00000	0.000000		0.000000		0.000000	
1	0.00000	0.000000		0.000000		0.000000	
2	42.29631	208.168976		4053.578857		112.404037	
3	16.77198	95.327438		3838.189453		155.573868	
4	0.00000	0.000000		0.000000		0.000000	
	time_of_day_mean	weekday_mean	quarter_mean	relative_date_PCIAT_mean	\		
0	0.000000e+00	0.000000		0.0		0.000000	
1	0.000000e+00	0.000000		0.0		0.000000	
2	5.046215e+13	4.470182		3.0		53.201683	
3	4.321212e+13	3.909848		3.0		79.435593	
4	0.000000e+00	0.000000		0.0		0.000000	
	fourier_X_real	fourier_X_imag	fourier_Y_real	fourier_Y_imag	\		
0	0.000000	0.000000e+00		0.000000		0.000000	
1	0.000000	0.000000e+00		0.000000		0.000000	
2	-2653.531675	-1.083578e-14	705.803060	-207.446683			
3	4103.865122	-1.680035e+03	14385.071425	3120.930726			
4	0.000000	0.000000e+00		0.000000		0.000000	
	fourier_Z_real	fourier_Z_imag	activity_during_day	activity_during_night	\		
0	0.000000	0.000000e+00		0.0		0.000000	
1	0.000000	0.000000e+00		0.0		0.000000	
2	1995.401835	-5.684342e-15		0.0		2053.305176	
3	-26765.674436	-8.731149e-12		0.0		4727.518555	
4	0.000000	0.000000e+00		0.0		0.000000	
	activity_ratio_day_night	non_wear_proportion	sedentary_proportion	\			
0	0.0	0.000000		0.000000		0.000000	
1	0.0	0.000000		0.000000		0.000000	
2	0.0	0.000000		0.000000		0.792453	
3	0.0	0.655708				0.978501	
4	0.0	0.000000		0.000000		0.000000	
	light_activity_proportion	moderate_activity_proportion	\				

```
0          0.000000          0.000000
1          0.000000          0.000000
2          0.198131          0.007870
3          0.021171          0.000288
4          0.000000          0.000000
```

```
vigorous_activity_proportion  actigraphy_present
0          0.000000          0
1          0.000000          0
2          0.001546          1
3          0.000040          1
4          0.000000          0
```

```
[74]: list(oversampled_df.columns)
```

```
['Basic_Demos-Enroll_Season',
 'Basic_Demos-Age',
 'Basic_Demos-Sex',
 'CGAS-Season',
 'CGAS-CGAS_Score',
 'Physical-Season',
 'Physical-BMI',
 'Physical-Height',
 'Physical-Weight',
 'Physical-Waist_Circumference',
 'Physical-Diastolic_BP',
 'Physical-HeartRate',
 'Physical-Systolic_BP',
 'Fitness_Endurance-Season',
 'Fitness_Endurance-Max_Stage',
 'Fitness_Endurance-Time_Mins',
 'Fitness_Endurance-Time_Sec',
 'FGC-Season',
 'FGC-FGC CU',
 'FGC-FGC CU_Zone',
 'FGC-FGC GSND',
 'FGC-FGC GSND_Zone',
 'FGC-FGC GSD',
 'FGC-FGC GSD_Zone',
 'FGC-FGC PU',
 'FGC-FGC PU_Zone',
 'FGC-FGC SRL',
 'FGC-FGC SRL_Zone',
 'FGC-FGC SRR',
 'FGC-FGC SRR_Zone',
 'FGC-FGC TL',
 'FGC-FGC TL_Zone',
```

'BIA-Season',
'BIA-BIA_Activity_Level_num',
'BIA-BIA_BMC',
'BIA-BIA_BMI',
'BIA-BIA_BMR',
'BIA-BIA_DEE',
'BIA-BIA_ECW',
'BIA-BIA_FFM',
'BIA-BIA_FFMI',
'BIA-BIA_FMI',
'BIA-BIA_Fat',
'BIA-BIA_Frame_num',
'BIA-BIA_ICW',
'BIA-BIA_LDM',
'BIA-BIA_LST',
'BIA-BIA_SMM',
'BIA-BIA_TBW',
'PAQ_A-Season',
'PAQ_A-PAQ_A_Total',
'PAQ_C-Season',
'PAQ_C-PAQ_C_Total',
'PCIAT-PCIAT_Total',
'SDS-Season',
'SDS-SDS_Total_Raw',
'SDS-SDS_Total_T',
'PreInt_EduHx-Season',
'PreInt_EduHx-computerinternet_hoursday',
'Age_Group',
'PCIAT_Cluster',
'CGAS-CGAS_Score_x_SDS-SDS_Total_Raw',
'CGAS-CGAS_Score_x_Physical-BMI',
'X_mean',
'X_std',
'X_min',
'X_max',
'Y_mean',
'Y_std',
'Y_min',
'Y_max',
'Z_mean',
'Z_std',
'Z_min',
'Z_max',
'enmo_mean',
'enmo_std',
'anglez_mean',
'anglez_std',

```

'non-wear_flag_mean',
'light_mean',
'light_std',
'battery_voltage_mean',
'battery_voltage_std',
'time_of_day_mean',
'weekday_mean',
'quarter_mean',
'relative_date_PCIAT_mean',
'fourier_X_real',
'fourier_X_imag',
'fourier_Y_real',
'fourier_Y_imag',
'fourier_Z_real',
'fourier_Z_imag',
'activity_during_day',
'activity_during_night',
'activity_ratio_day_night',
'non_wear_proportion',
'sedentary_proportion',
'light_activity_proportion',
'moderate_activity_proportion',
'vegrous_activity_proportion',
'actigraphy_present',
'sii',
'id']

```

```

[75]: # Step 1: Create sets of columns for easier comparison
oversampled_columns_set = set(oversampled_df.columns)
merged_test_columns_set = set(merged_test_df.columns)

# Step 2: Identify shared columns
shared_columns = list(oversampled_columns_set.
                     & intersection(merged_test_columns_set))
print(f"Shared Columns between oversampled_df and merged_test_df:
      \n{shared_columns}\n")

# Step 3: Identify columns present in oversampled_df but missing in
#         merged_test_df
missing_in_test_df = list(oversampled_columns_set - merged_test_columns_set)
print(f"Columns in oversampled_df but missing in merged_test_df:
      \n{missing_in_test_df}\n")

# Step 4: Identify additional columns present in merged_test_df but not in
#         oversampled_df
additional_in_test_df = list(merged_test_columns_set - oversampled_columns_set)

```

```

print(f"Additional Columns in merged_test_df not in oversampled_df:
    ↪\n{additional_in_test_df}\n")

# Step 5: Filter out columns that cannot be used in training due to missing
    ↪target variables like 'sii'
# Remove columns such as 'sii' which are only relevant during training, not in
    ↪the test set
excluded_columns = ['sii', 'PCIAT-PCIAT_Total', 'PCIAT_Cluster']

# Determine final columns for training based on shared columns, excluding any
    ↪that are in the excluded list
final_student_training_columns = [col for col in shared_columns if col not in
    ↪excluded_columns]
print(f"Final Columns to be used for training the student model:
    ↪\n{final_student_training_columns}\n")

# Step 6: (Optional) Create placeholders for missing columns if necessary
# For columns that are required but missing, we can fill with zeros or mean
    ↪values (if numeric), or a special placeholder for categoricals
for col in missing_in_test_df:
    if col not in excluded_columns: # Avoid creating placeholders for excluded
        ↪columns
        # Create a placeholder column (e.g., filling with zeros)
        if col in oversampled_df.select_dtypes(include=[np.number]).columns:
            merged_test_df[col] = 0 # Fill missing numeric columns with zero
        else:
            merged_test_df[col] = 'missing' # Fill missing categorical columns
        ↪with a placeholder
        print(f"Created placeholder for missing column: {col}")

# Step 7: Select the final subset of columns from merged_test_df for training
    ↪the student model
final_student_model_df = merged_test_df[final_student_training_columns]
print(f"Shape of final dataframe for student model training:
    ↪{final_student_model_df.shape}")

```

Shared Columns between oversampled_df and merged_test_df:

```

['BIA-BIA_SMM', 'BIA-BIA_FMI', 'Fitness_Endurance-Season', 'Y_mean', 'Z_min',
'CGAS-Season', 'BIA-BIA_Fat', 'FGC-FGC_GSD', 'X_max', 'battery_voltage_mean',
'PreInt_EduHx-computerinternet_hoursday', 'quarter_mean', 'fourier_Z_real',
'Fitness_Endurance-Time_Mins', 'BIA-BIA_DEE', 'X_min', 'Y_min', 'Age_Group',
'BIA-BIA_ECW', 'fourier_Y_imag', 'FGC-FGC_GSND_Zone', 'anglez_std', 'enmo_std',
'battery_voltage_std', 'X_mean', 'BIA-BIA_Activity_Level_num', 'FGC-
FGC_SRR_Zone', 'CGAS-CGAS_Score', 'Y_max', 'SDS-SDS_Total_Raw', 'PAQ_C-Season',
'FGC-FGC_TL', 'BIA-BIA_BMC', 'fourier_Z_imag', 'PAQ_C-PAQ_C_Total', 'FGC-
FGC_CU_Zone', 'Basic_Demos-Age', 'FGC-FGC_GSD_Zone', 'FGC-FGC_TL_Zone', 'non-
wear_flag_mean', 'Physical-Waist_Circumference', 'fourier_X_imag', 'BIA-

```

```

BIA_BMI', 'actigraphy_present', 'FGC-FGC_CU', 'fourier_Y_real', 'BIA-BIA_TBW',
'activity_ratio_day_night', 'FGC-FGC_PU_Zone', 'Physical-Season', 'Physical-
Weight', 'Physical-HeartRate', 'activity_during_night', 'BIA-BIA_BMR',
'fourier_X_real', 'light_activity_proportion', 'BIA-BIA_FFM', 'moderate_activity_proportion', 'Z_std', 'Z_mean', 'anglez_mean', 'Physical-Diastolic_BP', 'BIA-BIA_Frame_num', 'Physical-BMI', 'sedentary_proportion', 'PAQ_A-Season', 'FGC-FGC_SRR', 'weekday_mean', 'Basic_Demos-Enroll_Season', 'FGC-FGC_SRL', 'FGC-FGC_SRL_Zone', 'BIA-BIA_ICW', 'Z_max', 'activity_during_day', 'SDS-SDS_Total_T', 'time_of_day_mean', 'PAQ_A-PAQ_A_Total', 'FGC-FGC_GSND', 'Physical-Systolic_BP', 'BIA-BIA_LDM', 'FGC-Season', 'id', 'relative_date_PCIAT_mean', 'BIA-Season', 'BIA-BIA_FFM', 'non_wear_proportion', 'Fitness_Endurance-Time_Sec', 'light_std', 'Physical-Height', 'PreInt_EduHx-Season', 'enmo_mean', 'Fitness_Endurance-Max_Stage', 'light_mean', 'Basic_Demos-Sex', 'Y_std', 'X_std', 'BIA-BIA_LST', 'FGC-FGC_PU', 'vigorous_activity_proportion', 'SDS-Season']

```

Columns in oversampled_df but missing in merged_test_df:

```

['PCIAT_Cluster', 'CGAS-CGAS_Score_x_SDSDS_Total_Raw', 'CGAS-
CGAS_Score_x_Physical-BMI', 'sii', 'PCIAT-PCIAT_Total']

```

Additional Columns in merged_test_df not in oversampled_df:

```

['Physical-Waist_Circumference_missing', 'PAQ_A-PAQ_A_Total_missing', 'PAQ_A-
Season_missing']

```

Final Columns to be used for training the student model:

```

['BIA-BIA_SMM', 'BIA-BIA_FMI', 'Fitness_Endurance-Season', 'Y_mean', 'Z_min',
'CGAS-Season', 'BIA-BIA_Fat', 'FGC-FGC_GSD', 'X_max', 'battery_voltage_mean',
'PreInt_EduHx-computerinternet_hoursday', 'quarter_mean', 'fourier_Z_real',
'Fitness_Endurance-Time_Mins', 'BIA-BIA_DEE', 'X_min', 'Y_min', 'Age_Group',
'BIA-BIA_ECW', 'fourier_Y_imag', 'FGC-FGC_GSND_Zone', 'anglez_std', 'enmo_std',
'battery_voltage_std', 'X_mean', 'BIA-BIA_Activity_Level_num', 'FGC-
FGC_SRR_Zone', 'CGAS-CGAS_Score', 'Y_max', 'SDS-SDS_Total_Raw', 'PAQ_C-Season',
'FGC-FGC_TL', 'BIA-BIA_BMC', 'fourier_Z_imag', 'PAQ_C-PAQ_C_Total', 'FGC-
FGC_CU_Zone', 'Basic_Demos-Age', 'FGC-FGC_GSD_Zone', 'FGC-FGC_TL_Zone', 'non-
wear_flag_mean', 'Physical-Waist_Circumference', 'fourier_X_imag', 'BIA-
BIA_BMI', 'actigraphy_present', 'FGC-FGC_CU', 'fourier_Y_real', 'BIA-BIA_TBW',
'activity_ratio_day_night', 'FGC-FGC_PU_Zone', 'Physical-Season', 'Physical-
Weight', 'Physical-HeartRate', 'activity_during_night', 'BIA-BIA_BMR',
'fourier_X_real', 'light_activity_proportion', 'BIA-BIA_FFM', 'moderate_activity_proportion', 'Z_std', 'Z_mean', 'anglez_mean', 'Physical-Diastolic_BP', 'BIA-BIA_Frame_num', 'Physical-BMI', 'sedentary_proportion', 'PAQ_A-Season', 'FGC-FGC_SRR', 'weekday_mean', 'Basic_Demos-Enroll_Season', 'FGC-FGC_SRL', 'FGC-FGC_SRL_Zone', 'BIA-BIA_ICW', 'Z_max', 'activity_during_day', 'SDS-SDS_Total_T', 'time_of_day_mean', 'PAQ_A-PAQ_A_Total', 'FGC-FGC_GSND', 'Physical-Systolic_BP', 'BIA-BIA_LDM', 'FGC-Season', 'id', 'relative_date_PCIAT_mean', 'BIA-Season', 'BIA-BIA_FFM', 'non_wear_proportion', 'Fitness_Endurance-Time_Sec', 'light_std', 'Physical-Height', 'PreInt_EduHx-Season', 'enmo_mean', 'Fitness_Endurance-Max_Stage',

```

```
'light_mean', 'Basic_Demos-Sex', 'Y_std', 'X_std', 'BIA-BIA_LST', 'FGC-FGC_PU',
'vigorous_activity_proportion', 'SDS-Season']
```

```
Created placeholder for missing column: CGAS-CGAS_Score_x_SDS-SDS_Total_Raw
Created placeholder for missing column: CGAS-CGAS_Score_x_Physical-BMI
Shape of final dataframe for student model training: (6, 100)
```

```
[76]: # Import necessary libraries for feature selection
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectKBest, f_classif
import pandas as pd

# Given: Excluded actigraphy-related columns
included_columns =['FGC-FGC_PU', 'Z_std', 'BIA-BIA_DEE', 'SDS-Season', ↵
↳ 'light_mean', ↵
                'BIA-BIA_BMR', 'BIA-BIA_ICW', 'FGC-FGC_GSD_Zone', ↵
↳ 'Physical-BMI', ↵
                'Y_min', 'sedentary_proportion', 'time_of_day_mean', ↵
↳ 'BIA-BIA_FMI', ↵
                'PAQ_C-PAQ_C_Total', 'Physical-Weight', ↵
↳ 'Fitness_Endurance-Max_Stage', ↵
                'FGC-FGC_TL', 'PAQ_A-PAQ_A_Total', 'X_mean', ↵
↳ 'vigorous_activity_proportion', ↵
                'BIA-BIA_ECW', 'non-wear_flag_mean', 'actigraphy_present', ↵
↳ 'FGC-FGC_SRR_Zone', ↵
                'fourier_X_imag', 'Y_std', 'SDS-SDS_Total_T', ↵
↳ 'Basic_Demos-Enroll_Season', ↵
                'BIA-BIA_LDM', 'Fitness_Endurance-Time_Mins', ↵
↳ 'Physical-Systolic_BP', 'Basic_Demos-Sex', ↵
                'FGC-FGC_SRL', 'Y_max', 'Z_max', 'fourier_Y_real', ↵
↳ 'FGC-FGC CU_Zone', 'PAQ_C-Season', ↵
                'non_wear_proportion', 'Age_Group', 'FGC-FGC_GSND_Zone', ↵
↳ 'quarter_mean', 'light_std', ↵
                'X_max', 'CGAS-Season', 'FGC-FGC_SRL_Zone', 'anglez_mean', ↵
↳ 'anglez_std', 'fourier_Z_real', ↵
                'enmo_std', 'FGC-FGC_GSD', 'X_min', 'BIA-Season', ↵
↳ 'FGC-FGC_PU_Zone', 'X_std', 'BIA-BIA_TBW', ↵
                'Physical-HeartRate', 'FGC-Season', ↵
↳ 'Fitness_Endurance-Time_Sec', 'activity_during_day', ↵
                'Y_mean', 'BIA-BIA_Activity_Level_num', 'FGC-FGC_SRR', ↵
↳ 'Z_min', 'PreInt_EduHx-Season', ↵
                'fourier_X_real', 'BIA-BIA_FFM', 'BIA-BIA_FFM', ↵
↳ 'BIA-BIA_SMM', 'activity_during_night', ↵
                'PAQ_A-Season', 'fourier_Z_imag', 'Physical-Diastolic_BP', ↵
↳ 'battery_voltage_mean', ↵
```

```

        'moderate_activity_proportion', 'Physical-Season',
↳ 'battery_voltage_std', 'BIA-BIA_Fat',
        'BIA-BIA_LST', 'PreInt_EduHx-computerinternet_hoursday',
↳ 'enmo_mean', 'FGC-FGC_TL_Zone',
        'BIA-BIA_Frame_num', 'weekday_mean',
↳ 'Fitness_Endurance-Season', 'Physical-Height',
        'FGC-FGC_GSND', 'fourier_Y_imag', 'BIA-BIA_BMI',
↳ 'SDS-SDS_Total_Raw',
        'Physical-Waist_Circumference', 'CGAS-CGAS_Score',
↳ 'relative_date_PCIAT_mean',
        'FGC-FGC CU', 'light_activity_proportion',
↳ 'activity_ratio_day_night', 'Z_mean',
        'BIA-BIA_BMC', 'Basic_Demos-Age']

# Load the oversampled_df DataFrame
# Make sure to replace 'oversampled_df' with your actual DataFrame variable
# Note: Exclude 'sii' (target) and 'id' (identifier) from features
#features_to_exclude = ['sii', 'id', 'actigraphy_present'] + actigraphy_columns
features_for_selection = oversampled_df[included_columns]
print(list(features_for_selection.columns))
target = oversampled_df['sii']

# Perform Tree-based Feature Selection using RandomForestClassifier
forest_model = RandomForestClassifier(random_state=42)
forest_model.fit(features_for_selection, target)

# Extract feature importances and sort them
feature_importances = pd.Series(forest_model.feature_importances_,
                                index=features_for_selection.columns)
sorted_importances = feature_importances.sort_values(ascending=False)

# Perform Univariate Feature Selection using SelectKBest with ANOVA F-test
k_best_selector = SelectKBest(score_func=f_classif, k=10) # Select top 10
↳ features
k_best_selector.fit(features_for_selection, target)

# Extract selected features
k_best_features = features_for_selection.columns[k_best_selector.get_support()]

# Store the results in a DataFrame for display
selected_features_df = pd.DataFrame({
    'Feature': features_for_selection.columns,
    'Importance_Score': feature_importances,
    'Selected_By_KBest': k_best_selector.get_support()
})

# Sort the DataFrame by importance score

```

```
selected_features_df = selected_features_df.sort_values(by='Importance_Score',  
                                                       ascending=False)
```

```
# Display the sorted feature importances and selected features using pandas  
print("Feature Selection Results:")  
print(selected_features_df)
```

```
['FGC-FGC_PU', 'Z_std', 'BIA-BIA_DEE', 'SDS-Season', 'light_mean', 'BIA-BIA_BMR', 'BIA-BIA_ICW', 'FGC-FGC_GSD_Zone', 'Physical-BMI', 'Y_min', 'sedentary_proportion', 'time_of_day_mean', 'BIA-BIA_FMI', 'PAQ_C-PAQ_C_Total', 'Physical-Weight', 'Fitness_Endurance-Max_Stage', 'FGC-FGC_TL', 'PAQ_A-PAQ_A_Total', 'X_mean', 'vigorous_activity_proportion', 'BIA-BIA_ECW', 'non-wear_flag_mean', 'actigraphy_present', 'FGC-FGC_SRR_Zone', 'fourier_X_imag', 'Y_std', 'SDS-SDS_Total_T', 'Basic_Demos-Enroll_Season', 'BIA-BIA_LDM', 'Fitness_Endurance-Time_Mins', 'Physical-Systolic_BP', 'Basic_Demos-Sex', 'FGC-FGC_SRL', 'Y_max', 'Z_max', 'fourier_Y_real', 'FGC-FGC CU_Zone', 'PAQ_C-Season', 'non_wear_proportion', 'Age_Group', 'FGC-FGC GSND_Zone', 'quarter_mean', 'light_std', 'X_max', 'CGAS-Season', 'FGC-FGC_SRL_Zone', 'anglez_mean', 'anglez_std', 'fourier_Z_real', 'enmo_std', 'FGC-FGC_GSD', 'X_min', 'BIA-Season', 'FGC-FGC_PU_Zone', 'X_std', 'BIA-BIA_TBW', 'Physical-HeartRate', 'FGC-Season', 'Fitness_Endurance-Time_Sec', 'activity_during_day', 'Y_mean', 'BIA-BIA_Activity_Level_num', 'FGC-FGC_SRR', 'Z_min', 'PreInt_EduHx-Season', 'fourier_X_real', 'BIA-BIA_FFM', 'BIA-BIA_FFM', 'BIA-BIA_SMM', 'activity_during_night', 'PAQ_A-Season', 'fourier_Z_imag', 'Physical-Diastolic_BP', 'battery_voltage_mean', 'moderate_activity_proportion', 'Physical-Season', 'battery_voltage_std', 'BIA-BIA_Fat', 'BIA-BIA_LST', 'PreInt_EduHx-computerinternet_hoursday', 'enmo_mean', 'FGC-FGC_TL_Zone', 'BIA-BIA_Frame_num', 'weekday_mean', 'Fitness_Endurance-Season', 'Physical-Height', 'FGC-FGC GSND', 'fourier_Y_imag', 'BIA-BIA_BMI', 'SDS-SDS_Total_Raw', 'Physical-Waist_Circumference', 'CGAS-CGAS_Score', 'relative_date_PCIAT_mean', 'FGC-FGC CU', 'light_activity_proportion', 'activity_ratio_day_night', 'Z_mean', 'BIA-BIA_BMC', 'Basic_Demos-Age']
```

Feature Selection Results:

	Feature
\	
Basic_Demos-Age	Basic_Demos-Age
BIA-BIA_LDM	BIA-BIA_LDM
Age_Group	Age_Group
PreInt_EduHx-computerinternet_hoursday	PreInt_EduHx-computerinternet_hoursday
Physical-Weight	Physical-Weight
...	...
fourier_X_imag	fourier_X_imag
non-wear_flag_mean	non-wear_flag_mean
actigraphy_present	actigraphy_present
activity_ratio_day_night	activity_ratio_day_night
activity_during_day	activity_during_day

Importance_Score Selected_By_KBest

```

Basic_Demos-Age          0.045561      True
BIA-BIA_LDM              0.034236      False
Age_Group                 0.032241      True
PreInt_EduHx-computerinternet_hoursday 0.025768      True
Physical-Weight           0.025649      True
...
...                      ...
fourier_X_imag           0.002257      False
non-wear_flag_mean        0.002081      False
actigraphy_present         0.000332      False
activity_ratio_day_night   0.000000      False
activity_during_day        0.000000      False

[99 rows x 3 columns]

/opt/conda/lib/python3.10/site-
packages/sklearn/feature_selection/_univariate_selection.py:112: UserWarning:
Features [59 95] are constant.

    warnings.warn("Features %s are constant." % constant_features_idx,
UserWarning)
/opt/conda/lib/python3.10/site-
packages/sklearn/feature_selection/_univariate_selection.py:113: RuntimeWarning:
invalid value encountered in divide
    f = msb / msw

```

[77]: selected_features_df.head()

```

[77]:                                         Feature
 \
Basic_Demos-Age          Basic_Demos-Age
BIA-BIA_LDM               BIA-BIA_LDM
Age_Group                  Age_Group
PreInt_EduHx-computerinternet_hoursday PreInt_EduHx-computerinternet_hoursday
Physical-Weight            Physical-Weight

                                         Importance_Score Selected_By_KBest
Basic_Demos-Age           0.045561      True
BIA-BIA_LDM                0.034236      False
Age_Group                   0.032241      True
PreInt_EduHx-computerinternet_hoursday 0.025768      True
Physical-Weight             0.025649      True

```

[82]: selected_features = features_for_selection.loc[:, k_best_selector.get_support()]
selected_features

```

[82]:      Physical-BMI  Physical-Weight  Age_Group  PAQ_A-Season  \
0       16.877316     50.800000  0.443345    0.480263
1       16.648696     75.600000  0.362030    0.480263
2       18.292347     81.600000  0.362030    0.480263

```

3	22.279952	112.200000	0.855589	0.480263
4	18.269958	83.565122	0.855589	0.480263
...
8207	21.591746	122.849976	0.965907	0.908433
8208	24.131142	159.969205	0.855589	0.893266
8209	23.879108	158.833890	0.865555	1.017185
8210	24.046040	133.743377	0.855589	0.480263
8211	19.869775	101.793592	0.855589	0.480263

	PreInt_EduHx-computerinternet_hoursday	Physical-Height	FGC-FGC_GSND \
0	3.000000	46.000000	12.457159
1	2.000000	56.500000	10.200000
2	0.000000	56.000000	15.489000
3	0.000000	59.500000	16.500000
4	0.000000	55.568097	19.270922
...
8207	2.000000	63.155757	24.573501
8208	2.000000	68.269205	37.768842
8209	2.084328	68.373508	39.950756
8210	0.767371	61.822798	23.801864
8211	2.753714	59.891713	16.584285

	BIA-BIA_BMI	FGC-FGC CU	Basic_Demos-Age
0	16.879200	0.000000	5.000000
1	18.540298	20.000000	10.000000
2	18.294300	18.000000	9.000000
3	30.186500	12.000000	13.000000
4	18.540307	10.701686	11.000000
...
8207	21.644003	35.757071	16.800417
8208	24.184481	14.154304	14.538411
8209	23.888294	11.517900	15.168656
8210	24.336307	16.272720	13.383686
8211	19.771615	27.462860	12.507428

[8212 rows x 10 columns]

```
[81]: from tensorflow.keras.layers import Dense, Dropout, BatchNormalization, Input, ↴
    ↴LeakyReLU, ELU # Include ELU here
from tensorflow.keras.models import Model
from tensorflow.keras.losses import CategoricalCrossentropy, KLDivergence
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score, f1_score
import numpy as np
```

```

# Extract the selected features (using SelectKBest results)
selected_features = features_for_selection.loc[:, k_best_selector.get_support()]

print(selected_features.columns)
# Define input features and target
X = oversampled_df[selected_features.columns] # Use columns of selected
# features (non-actigraphy features)
y = oversampled_df['sii']

# Split the data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,
random_state=42)

# One-hot encode the labels for training
y_train_onehot = tf.keras.utils.to_categorical(y_train, num_classes=4)
y_val_onehot = tf.keras.utils.to_categorical(y_val, num_classes=4)

# Precompute teacher model predictions using the full feature set (102 features)
teacher_full_X = oversampled_df.drop(columns=['sii', 'id',
# 'actigraphy_present']) # Use all features except target and ID
teacher_full_preds = teacher_model_A.predict(teacher_full_X) # Get softmax
# outputs

# Match the teacher predictions to the training and validation sets based on
# indices
teacher_train_preds = teacher_full_preds[y_train.index] # Teacher predictions
# for training data
teacher_val_preds = teacher_full_preds[y_val.index] # Teacher predictions
# for validation data

# Create a TensorFlow variable to hold the teacher predictions for the current
# batch
teacher_train_preds_tensor = tf.convert_to_tensor(teacher_train_preds, dtype=tf.
float32)

# Custom loss function combining categorical cross-entropy and KL Divergence
def custom_loss(teacher_preds_tensor):
    @tf.function
    def loss_fn(y_true, y_pred):
        # Get the current batch size
        batch_size = tf.shape(y_pred)[0]

        # Select the corresponding teacher predictions for the current batch
        teacher_preds_batch = teacher_preds_tensor[:batch_size]

        # Calculate categorical cross-entropy loss

```

```

cce_loss = CategoricalCrossentropy()(y_true, y_pred)

# Calculate KL Divergence loss between student predictions and teacher  

outputs
kl_loss = KLDivergence()(teacher_preds_batch, y_pred)

# Combine the two losses with equal weight (0.5 each)
return 0.5 * cce_loss + 0.5 * kl_loss

return loss_fn

# Create the student model
def create_student_model(input_shape):
    inputs = Input(shape=(input_shape,))
    x = Dense(64, activation='linear', kernel_regularizer=tf.keras.regularizers.
l2(0.002))(inputs)
    #x = LeakyReLU(alpha=0.1)(x)
    x = BatchNormalization()(x)
    x = Dropout(0.4)(x)

    x = Dense(32, activation='linear', kernel_regularizer=tf.keras.regularizers.
l2(0.002))(x)
    x = LeakyReLU(alpha=0.1)(x)
    #x = BatchNormalization()(x)
    #x = Dropout(0.6)(x)

    # Additional layer for better capacity
    x = Dense(16, activation='linear', kernel_regularizer=tf.keras.regularizers.
l2(0.002))(x)
    x = ELU(alpha=1.0)(x)
    #x = BatchNormalization()(x)
    #x = Dropout(0.5)(x)

    x = Dense(8, activation='linear', kernel_regularizer=tf.keras.regularizers.
l2(0.002))(x)
    x = ELU(alpha=1.0)(x)

    outputs = Dense(4, activation='softmax')(x)

model = Model(inputs=inputs, outputs=outputs)

# Compile the model with the custom loss function and the specified  

optimizer
model.compile(optimizer=Adam(learning_rate=0.001),
loss=custom_loss(teacher_train_preds_tensor), metrics=['accuracy'])

```

```

    return model

# Create the student model using the dynamically determined input shape
student_model = create_student_model(X_train.shape[1])

improved_class_weight_dict = {0: 1.0, 1: 1.0, 2: 1.2, 3: 1.0}

# Early stopping callback
early_stopping = EarlyStopping(monitor='val_loss', patience=6, □
    ↴restore_best_weights=True)

# Train the student model
history = student_model.fit(
    X_train, y_train_onehot,
    validation_data=(X_val, y_val_onehot),
    epochs=50,
    batch_size=64,
    callbacks=[early_stopping],
    class_weight=improved_class_weight_dict,
    verbose=1
)

# Evaluate the student model on the validation set
student_val_predictions = student_model.predict(X_val)
student_val_pred_labels = np.argmax(student_val_predictions, axis=1)

# Calculate evaluation metrics
student_accuracy = accuracy_score(y_val, student_val_pred_labels)
student_f1 = f1_score(y_val, student_val_pred_labels, average='weighted')

print(f"Student Model Accuracy: {student_accuracy:.4f}")
print(f"Student Model F1-Score: {student_f1:.4f}")
print(f"Classification Report:\n{classification_report(y_val, □
    ↴student_val_pred_labels)}")

# Implement Quadratic Weighted Kappa Evaluation
def quadratic_weighted_kappa(y_true, y_pred, N=4):
    # Create matrices O, W, and E
    O = np.zeros((N, N))
    for a, p in zip(y_true, y_pred):
        O[a][p] += 1

    W = np.zeros((N, N))
    for i in range(N):
        for j in range(N):
            W[i][j] = ((i - j) ** 2) / (N - 1) ** 2

```

```

actual_hist = np.histogram(y_true, bins=np.arange(N + 1))[0]
pred_hist = np.histogram(y_pred, bins=np.arange(N + 1))[0]
E = np.outer(actual_hist, pred_hist) / np.sum(actual_hist)

# Calculate QWK
kappa = 1 - (np.sum(W * O) / np.sum(W * E))
return kappa

# Compute QWK for the student model
student_qwk = quadratic_weighted_kappa(y_val, student_val_pred_labels)
print(f"Student Model Quadratic Weighted Kappa (QWK): {student_qwk:.4f}")

```

```

Index(['Physical-BMI', 'Physical-Weight', 'Age_Group', 'PAQ_A-Season',
       'PreInt_EduHx-computerinternet_hoursday', 'Physical-Height',
       'FGC-FGC_GSN', 'BIA-BIA_BMI', 'FGC-FGC_CU', 'Basic_Demos-Age'],
      dtype='object')
257/257          0s 1ms/step
Epoch 1/50

/opt/conda/lib/python3.10/site-
packages/keras/src/layers/activations/leaky_relu.py:41: UserWarning: Argument
`alpha` is deprecated. Use `negative_slope` instead.
  warnings.warn(
103/103          2s 5ms/step -
accuracy: 0.3437 - loss: 1.4683 - val_accuracy: 0.3488 - val_loss: 1.3621
Epoch 2/50
103/103          0s 2ms/step -
accuracy: 0.4743 - loss: 1.2830 - val_accuracy: 0.4090 - val_loss: 1.2159
Epoch 3/50
103/103          0s 2ms/step -
accuracy: 0.4867 - loss: 1.2510 - val_accuracy: 0.4577 - val_loss: 1.1786
Epoch 4/50
103/103          0s 2ms/step -
accuracy: 0.5152 - loss: 1.2273 - val_accuracy: 0.5362 - val_loss: 1.1637
Epoch 5/50
103/103          0s 2ms/step -
accuracy: 0.5296 - loss: 1.2100 - val_accuracy: 0.4741 - val_loss: 1.1449
Epoch 6/50
103/103          0s 2ms/step -
accuracy: 0.5491 - loss: 1.1971 - val_accuracy: 0.4425 - val_loss: 1.1373
Epoch 7/50
103/103          0s 2ms/step -
accuracy: 0.5445 - loss: 1.1842 - val_accuracy: 0.5727 - val_loss: 1.1212
Epoch 8/50
103/103          0s 2ms/step -
accuracy: 0.5573 - loss: 1.1675 - val_accuracy: 0.5417 - val_loss: 1.1136
Epoch 9/50
103/103          0s 2ms/step -

```

```
accuracy: 0.5690 - loss: 1.1575 - val_accuracy: 0.5265 - val_loss: 1.1198
Epoch 10/50
103/103          0s 2ms/step -
accuracy: 0.5644 - loss: 1.1515 - val_accuracy: 0.4760 - val_loss: 1.1160
Epoch 11/50
103/103          0s 2ms/step -
accuracy: 0.5778 - loss: 1.1421 - val_accuracy: 0.5575 - val_loss: 1.0925
Epoch 12/50
103/103          0s 2ms/step -
accuracy: 0.5773 - loss: 1.1288 - val_accuracy: 0.5703 - val_loss: 1.0971
Epoch 13/50
103/103          0s 2ms/step -
accuracy: 0.5818 - loss: 1.1259 - val_accuracy: 0.4632 - val_loss: 1.0959
Epoch 14/50
103/103          0s 2ms/step -
accuracy: 0.5789 - loss: 1.1276 - val_accuracy: 0.4948 - val_loss: 1.0995
Epoch 15/50
103/103          0s 2ms/step -
accuracy: 0.5880 - loss: 1.1257 - val_accuracy: 0.5721 - val_loss: 1.0725
Epoch 16/50
103/103          0s 2ms/step -
accuracy: 0.5907 - loss: 1.1176 - val_accuracy: 0.3743 - val_loss: 1.1253
Epoch 17/50
103/103          0s 2ms/step -
accuracy: 0.5964 - loss: 1.1171 - val_accuracy: 0.5405 - val_loss: 1.0851
Epoch 18/50
103/103          0s 2ms/step -
accuracy: 0.5943 - loss: 1.1162 - val_accuracy: 0.4680 - val_loss: 1.1174
Epoch 19/50
103/103          0s 2ms/step -
accuracy: 0.5717 - loss: 1.1184 - val_accuracy: 0.5697 - val_loss: 1.0663
Epoch 20/50
103/103          0s 2ms/step -
accuracy: 0.5796 - loss: 1.1154 - val_accuracy: 0.5161 - val_loss: 1.1162
Epoch 21/50
103/103          0s 2ms/step -
accuracy: 0.5939 - loss: 1.1137 - val_accuracy: 0.5612 - val_loss: 1.0818
Epoch 22/50
103/103          0s 2ms/step -
accuracy: 0.5962 - loss: 1.1084 - val_accuracy: 0.6403 - val_loss: 1.0640
Epoch 23/50
103/103          0s 2ms/step -
accuracy: 0.5893 - loss: 1.1123 - val_accuracy: 0.5770 - val_loss: 1.0610
Epoch 24/50
103/103          0s 2ms/step -
accuracy: 0.5934 - loss: 1.1090 - val_accuracy: 0.5247 - val_loss: 1.0870
Epoch 25/50
103/103          0s 2ms/step -
```

```

accuracy: 0.5992 - loss: 1.1081 - val_accuracy: 0.5222 - val_loss: 1.0904
Epoch 26/50
103/103          0s 2ms/step -
accuracy: 0.5926 - loss: 1.1090 - val_accuracy: 0.4857 - val_loss: 1.0692
Epoch 27/50
103/103          0s 2ms/step -
accuracy: 0.5957 - loss: 1.1108 - val_accuracy: 0.5654 - val_loss: 1.0614
Epoch 28/50
103/103          0s 2ms/step -
accuracy: 0.5954 - loss: 1.1112 - val_accuracy: 0.4997 - val_loss: 1.0842
Epoch 29/50
103/103          0s 2ms/step -
accuracy: 0.5899 - loss: 1.1117 - val_accuracy: 0.4334 - val_loss: 1.1042
52/52          0s 2ms/step
Student Model Accuracy: 0.5770
Student Model F1-Score: 0.5355
Classification Report:
      precision    recall   f1-score   support
      0         0.52     0.82     0.64      418
      1         0.45     0.17     0.25      407
      2         0.62     0.40     0.49      416
      3         0.66     0.91     0.77      402
      accuracy           0.58      1643
      macro avg       0.56     0.58     0.54      1643
      weighted avg    0.56     0.58     0.54      1643

```

Student Model Quadratic Weighted Kappa (QWK): 0.7245

[79]: oversampled_df['sii'].value_counts()

[79]: sii

2	2053
0	2053
1	2053
3	2053

Name: count, dtype: int64

[94]: merged_test_df.head(20)

[94]:

	id	Basic_Demos-Enroll_Season	Basic_Demos-Age	Basic_Demos-Sex	\
0	00008ff9	Fall	5.0	0.0	
1	00105258	Summer	10.0	1.0	
2	00115b9f	Winter	9.0	0.0	
3	001f3379	Spring	13.0	1.0	
4	00abe655	Fall	11.0	0.0	
5	00d56d4b	Spring	5.0	1.0	

	CGAS-Season	CGAS-CGAS_Score	Physical-Season	Physical-BMI	Physical-Height	\
0	Winter	51.0	Fall	16.877316	46.000000	
1	Fall	71.0	Fall	16.648696	56.500000	
2	Fall	71.0	Summer	18.292347	56.000000	
3	Winter	50.0	Summer	22.279952	59.500000	
4	Summer	66.0	Fall	17.864055	53.089389	
5	Summer	80.0	Spring	17.284504	44.000000	
	Physical-Weight	Physical-Waist_Circumference	Physical-Diastolic_BP			\
0	50.800000		NaN	76.659994		
1	75.600000		NaN	65.000000		
2	81.600000		NaN	60.000000		
3	112.200000		NaN	60.000000		
4	73.360103		NaN	64.906547		
5	47.600000		NaN	61.000000		
	Physical-HeartRate	Physical-Systolic_BP	Fitness_Endurance-Season	\		
0	42.625084	95.537106		Fall		
1	94.000000	117.000000		Fall		
2	97.000000	117.000000		Summer		
3	73.000000	102.000000		Fall		
4	79.417997	109.671015		Fall		
5	76.000000	109.000000		Spring		
	Fitness_Endurance-Max_Stage	Fitness_Endurance-Time_Mins		\		
0	0.108192		-2.783656			
1	5.000000		7.000000			
2	6.000000		9.000000			
3	8.161510		13.323058			
4	4.434398		5.868766			
5	2.625106		2.250025			
	Fitness_Endurance-Time_Sec	FGC-Season	FGC-FGC CU	FGC-FGC CU_Zone	\	
0	13.432611	Fall	0.000000	0.00000		
1	33.000000	Fall	20.000000	1.00000		
2	37.000000	Summer	18.000000	1.00000		
3	45.646307	Summer	12.000000	0.00000		
4	30.737339	Winter	11.771994	0.48317		
5	23.498683	Spring	0.000000	0.00000		
	FGC-FGC_GSND	FGC-FGC_GSND_Zone	FGC-FGC_GSD	FGC-FGC_GSD_Zone	FGC-FGC_PU	\
0	3.706899	-0.030646	11.401920		2.0	0.000000
1	10.200000	1.000000	14.700000		2.0	7.000000
2	11.694644	1.237246	15.459184		2.0	5.000000
3	16.500000	2.000000	17.900000		2.0	6.000000
4	9.702796	0.921081	14.447450		2.0	4.413705

5	6.372775	0.392507	12.755998	2.0	0.000000	
0	FGC-FGC_PU_Zone	FGC-FGC_SRL	FGC-FGC_SRL_Zone	FGC-FGC_SRR	\	
0	0.000000	7.000000	0.000000	6.000000		
1	1.000000	10.000000	1.000000	10.000000		
2	0.000000	7.000000	0.000000	7.000000		
3	0.000000	10.000000	1.000000	11.000000		
4	0.458711	9.593142	0.832517	9.539816		
5	0.000000	10.500000	1.000000	10.000000		
0	FGC-FGC_SRR_Zone	FGC-FGC_TL	FGC-FGC_TL_Zone	BIA-Season	\	
0	0.000000	6.000000	1.000000	Fall		
1	1.000000	5.000000	0.000000	Summer		
2	0.000000	7.000000	1.000000	Summer		
3	1.000000	8.000000	0.000000	Summer		
4	0.834634	6.11333	0.357534	Summer		
5	1.000000	7.000000	1.000000	Summer		
0	BIA-BIA_Activity_Level_num	BIA-BIA_BMC	BIA-BIA_BMI	BIA-BIA_BMR	\	
0	2.000000	2.668550	16.879200	932.498000		
1	2.940449	3.641048	17.160848	1087.854533		
2	3.000000	3.841910	18.294300	1131.430000		
3	2.000000	4.330360	30.186500	1330.970000		
4	2.634960	3.539088	18.782182	1087.500178		
5	2.932333	3.170967	13.459508	968.943255		
0	BIA-BIA_DEE	BIA-BIA_ECW	BIA-BIA_FFM	BIA-BIA_FFFI	BIA-BIA_FMI	\
0	1492.000000	8.255980	41.586200	13.817700	3.061430	
1	1858.417991	13.394408	58.139277	13.825440	3.303771	
2	1923.440000	15.592500	62.775700	14.074000	4.220330	
3	1996.450000	30.212400	84.028500	16.687700	13.498800	
4	1803.297738	14.468455	58.086989	14.178944	4.520419	
5	1707.997278	6.780333	45.387093	12.955624	0.141155	
0	BIA-BIA_Fat	BIA-BIA_Frame_num	BIA-BIA_ICW	BIA-BIA_LDM	BIA-BIA_LST	\
0	9.213770	1.000000	24.434900	8.895360	38.917700	
1	13.482399	1.863178	29.381756	15.362565	54.493534	
2	18.824300	2.000000	30.404100	16.779000	58.933800	
3	67.971500	2.000000	32.914100	20.902000	79.698200	
4	19.377546	1.710098	28.844178	14.773667	54.540391	
5	-4.415591	1.566602	26.842912	11.761994	42.191669	
0	BIA-BIA_SMM	BIA-BIA_TBW	PAQ_A-Season	PAQ_A-PAQ_A_Total	PAQ_C-Season	\
0	19.541300	32.690900	NaN	NaN	Winter	
1	24.801015	42.771962	NaN	NaN	Summer	
2	26.479800	45.996600	NaN	NaN	Winter	
3	35.380400	63.126500	NaN	NaN	Spring	

4	25.072255	43.300657	NaN	NaN	Winter		
5	20.013959	33.568832	NaN	NaN	Winter		
PAQ_C-PAQ_C_Total	SDS-Season	SDS-SDS_Total_Raw	SDS-SDS_Total_T	\			
0	-2.892886	Summer	65.892149	89.323116			
1	2.170000	Fall	38.000000	54.000000			
2	2.451000	Summer	31.000000	45.000000			
3	4.110000	Summer	40.000000	56.000000			
4	1.100000	Winter	42.000000	59.000000			
5	-1.349256	Spring	37.000000	53.000000			
PreInt_EduHx-Season	PreInt_EduHx-computerinternet_hoursday	Age_Group	\				
0	Fall	3.0	5-10				
1	Summer	2.0	5-10				
2	Winter	0.0	5-10				
3	Spring	0.0	11-15				
4	Fall	0.0	11-15				
5	Spring	0.0	5-10				
Physical-Waist_Circumference_missing	PAQ_A-Season_missing	\					
0	1	1					
1	1	1					
2	1	1					
3	1	1					
4	1	1					
5	1	1					
PAQ_A-PAQ_A_Total_missing	X_mean	X_std	X_min	X_max	\		
0	1 0.000000	0.000000	0.000000	0.000000	0.000000		
1	1 0.000000	0.000000	0.000000	0.000000	0.000000		
2	1 -0.316384	0.453665	-1.746094	1.507865			
3	1 -0.004272	0.351545	-1.038711	1.034351			
4	1 0.000000	0.000000	0.000000	0.000000	0.000000		
5	1 0.000000	0.000000	0.000000	0.000000	0.000000		
Y_mean	Y_std	Y_min	Y_max	Z_mean	Z_std	Z_min	\
0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.016009	0.502702	-2.905339	1.666354	-0.167890	0.585710	-1.048372
3	0.016859	0.303812	-1.522690	1.946303	-0.631731	0.623476	-1.018787
4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
5	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Z_max	enmo_mean	enmo_std	anglez_mean	anglez_std	non-wear_flag_mean	\	
0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2	1.546979	0.047388	0.106351	-10.580416	42.947170	0.000000	

3	1.146284	0.011926	0.024331	-55.630768	50.303635	0.655708
4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
5	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	light_mean	light_std	battery_voltage_mean	battery_voltage_std		\
0	0.00000	0.000000	0.000000	0.000000	0.000000	
1	0.00000	0.000000	0.000000	0.000000	0.000000	
2	42.29631	208.168976	4053.578857	112.404037		
3	16.77198	95.327438	3838.189453	155.573868		
4	0.00000	0.000000	0.000000	0.000000	0.000000	
5	0.00000	0.000000	0.000000	0.000000	0.000000	
	time_of_day_mean	weekday_mean	quarter_mean	relative_date_PCIAT_mean		\
0	0.000000e+00	0.000000	0.0	0.000000		
1	0.000000e+00	0.000000	0.0	0.000000		
2	5.046215e+13	4.470182	3.0	53.201683		
3	4.321212e+13	3.909848	3.0	79.435593		
4	0.000000e+00	0.000000	0.0	0.000000		
5	0.000000e+00	0.000000	0.0	0.000000		
	fourier_X_real	fourier_X_imag	fourier_Y_real	fourier_Y_imag		\
0	0.000000	0.000000e+00	0.000000	0.000000		
1	0.000000	0.000000e+00	0.000000	0.000000		
2	-2653.531675	-1.083578e-14	705.803060	-207.446683		
3	4103.865122	-1.680035e+03	14385.071425	3120.930726		
4	0.000000	0.000000e+00	0.000000	0.000000		
5	0.000000	0.000000e+00	0.000000	0.000000		
	fourier_Z_real	fourier_Z_imag	activity_during_day	activity_during_night		\
0	0.000000	0.000000e+00	0.0	0.000000		
1	0.000000	0.000000e+00	0.0	0.000000		
2	1995.401835	-5.684342e-15	0.0	2053.305176		
3	-26765.674436	-8.731149e-12	0.0	4727.518555		
4	0.000000	0.000000e+00	0.0	0.000000		
5	0.000000	0.000000e+00	0.0	0.000000		
	activity_ratio_day_night	non_wear_proportion	sedentary_proportion			\
0	0.0	0.000000	0.000000			
1	0.0	0.000000	0.000000			
2	0.0	0.000000	0.792453			
3	0.0	0.655708	0.978501			
4	0.0	0.000000	0.000000			
5	0.0	0.000000	0.000000			
	light_activity_proportion	moderate_activity_proportion				\
0	0.000000	0.000000				
1	0.000000	0.000000				

```

2          0.198131          0.007870
3          0.021171          0.000288
4          0.000000          0.000000
5          0.000000          0.000000

    vigorous_activity_proportion  actigraphy_present \
0                  0.000000          0
1                  0.000000          0
2                  0.001546          1
3                  0.000040          1
4                  0.000000          0
5                  0.000000          0

CGAS-CGAS_Score_x_SDS-SDS_Total_Raw  CGAS-CGAS_Score_x_Physical-BMI
0                      0                      0
1                      0                      0
2                      0                      0
3                      0                      0
4                      0                      0
5                      0                      0

```

[97]: # Ensure that the feature columns are of numeric type (float32) before making predictions

```

X_test = merged_test_df[selected_features_list].copy()

# Convert categorical columns in X_test to numerical types if necessary
for col in X_test.select_dtypes(include=['category', 'object']).columns:
    # Convert categorical values to numeric using the category codes or an appropriate mapping
    X_test[col] = X_test[col].astype('category').cat.codes

# Convert the entire DataFrame to float32 type to match the model's expected input type
X_test = X_test.astype('float32')

# Step 2: Use the final student model to make predictions on merged_test_df
test_predictions = student_model.predict(X_test)

# Step 3: Convert softmax predictions to class labels (integers)
predicted_labels = np.argmax(test_predictions, axis=1)

# Step 4: Create a DataFrame with 'id' and 'sii' columns
submission_df = merged_test_df[['id']].copy() # Copy the 'id' column from merged_test_df
submission_df['sii'] = predicted_labels # Add the predicted 'sii' values

# Step 5: Save the result as a CSV file with header

```

```
#submission_df.to_csv('imported/output/sample_submission.csv', index=False)

#print("sample_submission.csv created successfully.")
```

1/1 0s 21ms/step

[100]: X_test.head(10)

```
[100]:    Physical-BMI  Physical-Weight  Age_Group  PAQ_A-Season \
0      16.877316      50.799999      0.0        NaN
1      16.648697      75.599998      0.0        NaN
2      18.292347      81.599998      0.0        NaN
3      22.279951     112.199997      1.0        NaN
4      17.864056      73.360100      1.0        NaN
5      17.284504      47.599998      0.0        NaN

   PreInt_EduHx-computerinternet_hoursday  Physical-Height  FGC-FGC_GSND \
0                           3.0          46.00000       3.706898
1                           2.0          56.50000      10.200000
2                           0.0          56.00000      11.694644
3                           0.0          59.50000      16.500000
4                           0.0          53.08939      9.702796
5                           0.0          44.00000      6.372775

   BIA-BIA_BMI  FGC-FGC_CU  Basic_Demos-Age
0      16.879200      0.000000          5.0
1      17.160849      20.000000         10.0
2      18.294300      18.000000          9.0
3      30.186501      12.000000         13.0
4      18.782181     11.771994         11.0
5      13.459508      0.000000          5.0
```

[98]: submission_df.head(12)

```
[98]:      id  sii
0  00008ff9    0
1  00105258    0
2  00115b9f    0
3  001f3379    0
4  00abe655    0
5  00d56d4b    0
```