```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.gridspec as gridspec
import seaborn as sns
import warnings

warnings.filterwarnings('ignore', category=FutureWarning)

sns.set(style="whitegrid")
%matplotlib inline
```

Understanding the task

The aim of this competition is to predict the Severity Impairment Index (sii), which measures the level of problematic internet use among children and adolescents, based on physical activity data and other features.

sii is derived from `PCIAT-PCIAT_Total`, the sum of scores from the Parent-Child Internet Addiction Test (PCIAT: 20 questions, scored 0-5).

Target Variable (sii) is defined as:

- 0: None (PCIAT-PCIAT_Total from 0 to 30)
- 1: Mild (PCIAT-PCIAT_Total from 31 to 49)
- 2: Moderate (PCIAT-PCIAT_Total from 50 to 79)
- 3: Severe (PCIAT-PCIAT_Total 80 and more)

This makes sii an ordinal categorical variable with four levels, where the order of categories is meaningful.

Type of Machine Learning Problem we can use with sii as a target:

1. Ordinal classification (ordinal logistic regression, models with custom ordinal loss functions)
2. Multiclass classification (treat sii as a nominal categorical variable without considering the order)
3. Regression (ignore the discrete nature of categories and treat sii as a continuous variable, then round prediction)
4. Custom (e.g. loss functions that penalize errors based on the distance between categories)

We can also use `PCIAT-PCIAT_Total` as a continuous target variable, and implement regression on `PCIAT-PCIAT_Total` and then map predictions to sii categories.

Finally, another strategy involves predicting responses to each question of the Parent-Child Internet Addiction Test: i.e. pedict individual question scores as separate targets, sum the predicted scores to get the `PCIAT-PCIAT_Total` and map predictions to the corresponding sii category.

But first, let's make some exploratory data analysis.

Data Preview

```
train = pd.read_csv('/kaggle/input/child-mind-institute-problematic-internet-use/train.csv')
test = 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 data

```
display(train.head())
print(f"Train shape: {train.shape}")
```

```
         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  ...  PCIAT-PCIAT_18  PCIAT-PCIAT_19  PCIAT-PCIAT_20  \
0             50.8  ...             4.0             2.0             4.0
1             46.0  ...             0.0             0.0             0.0
2             75.6  ...             2.0             1.0
```

```
1.0
3            81.6  ...              3.0              4.0
1.0
4             NaN  ...              NaN              NaN
NaN

   PCIAT-PCIAT_Total SDS-Season  SDS-SDS_Total_Raw  SDS-SDS_Total_T  \
0               55.0        NaN                NaN              NaN
1                0.0       Fall               46.0             64.0
2               28.0       Fall               38.0             54.0
3               44.0     Summer               31.0             45.0
4                NaN        NaN                NaN              NaN

   PreInt_EduHx-Season PreInt_EduHx-computerinternet_hoursday  sii
0                 Fall                                    3.0  2.0
1               Summer                                    0.0  0.0
2               Summer                                    2.0  0.0
3               Winter                                    0.0  1.0
4                  NaN                                    NaN  NaN

[5 rows x 82 columns]

Train shape: (3960, 82)
```

Test data

```python
display(test.head())
print(f"Test shape: {test.shape}")
```

```
         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  ...  BIA-BIA_TBW  PAQ_A-Season  PAQ_A-PAQ_A_Total
\
0             50.8  ...      32.6909           NaN                NaN

1             46.0  ...      27.0552           NaN                NaN

2             75.6  ...          NaN           NaN                NaN

3             81.6  ...      45.9966           NaN                NaN

4              NaN  ...          NaN        Summer               1.04


   PAQ_C-Season PAQ_C-PAQ_C_Total  SDS-Season  SDS-SDS_Total_Raw  \
0           NaN               NaN         NaN                NaN
1          Fall             2.340        Fall               46.0
2        Summer             2.170        Fall               38.0
3        Winter             2.451      Summer               31.0
4           NaN               NaN         NaN                NaN

   SDS-SDS_Total_T PreInt_EduHx-Season  PreInt_EduHx-
computerinternet_hoursday
0              NaN                Fall
3.0
1             64.0              Summer
0.0
2             54.0              Summer
2.0
3             45.0              Winter
0.0
4              NaN                 NaN
NaN

[5 rows x 59 columns]

Test shape: (20, 59)
```

Data dictionary

```
data_dict.head()

                           Instrument                         Field  \
0                          Identifier                            id
1                        Demographics  Basic_Demos-Enroll_Season
2                        Demographics            Basic_Demos-Age
3                        Demographics            Basic_Demos-Sex
```

```
4  Children's Global Assessment Scale                CGAS-Season

                  Description              Type
Values  \
0         Participant's ID                  str
NaN
1     Season of enrollment                  str  Spring, Summer, Fall,
Winter
2       Age of participant                float
NaN
3       Sex of participant  categorical int
0,1
4  Season of participation                  str  Spring, Summer, Fall,
Winter

       Value Labels
0               NaN
1               NaN
2               NaN
3  0=Male, 1=Female
4               NaN
```

Helper functions

```
def calculate_stats(data, columns):
    if isinstance(columns, str):
        columns = [columns]

    stats = []
    for col in columns:
        if data[col].dtype in ['object', 'category']:
            counts = data[col].value_counts(dropna=False, sort=False)
            percents = data[col].value_counts(normalize=True,
dropna=False, sort=False) * 100
            formatted = counts.astype(str) + ' (' +
percents.round(2).astype(str) + '%)'
            stats_col = pd.DataFrame({'count (%)': formatted})
            stats.append(stats_col)
        else:
            stats_col = data[col].describe().to_frame().transpose()
            stats_col['missing'] = data[col].isnull().sum()
            stats_col.index.name = col
            stats.append(stats_col)

    return pd.concat(stats, axis=0)
```

Target Variables and Internet use

Let's identify the features that are related to the target variable and that are not present in the test set.

```python
train_cols = set(train.columns)
test_cols = set(test.columns)
columns_not_in_test = sorted(list(train_cols - test_cols))
data_dict[data_dict['Field'].isin(columns_not_in_test)]
```

```
                              Instrument              Field  \
54  Parent-Child Internet Addiction Test       PCIAT-Season
55  Parent-Child Internet Addiction Test     PCIAT-PCIAT_01
56  Parent-Child Internet Addiction Test     PCIAT-PCIAT_02
57  Parent-Child Internet Addiction Test     PCIAT-PCIAT_03
58  Parent-Child Internet Addiction Test     PCIAT-PCIAT_04
59  Parent-Child Internet Addiction Test     PCIAT-PCIAT_05
60  Parent-Child Internet Addiction Test     PCIAT-PCIAT_06
61  Parent-Child Internet Addiction Test     PCIAT-PCIAT_07
62  Parent-Child Internet Addiction Test     PCIAT-PCIAT_08
63  Parent-Child Internet Addiction Test     PCIAT-PCIAT_09
64  Parent-Child Internet Addiction Test     PCIAT-PCIAT_10
65  Parent-Child Internet Addiction Test     PCIAT-PCIAT_11
66  Parent-Child Internet Addiction Test     PCIAT-PCIAT_12
67  Parent-Child Internet Addiction Test     PCIAT-PCIAT_13
68  Parent-Child Internet Addiction Test     PCIAT-PCIAT_14
69  Parent-Child Internet Addiction Test     PCIAT-PCIAT_15
70  Parent-Child Internet Addiction Test     PCIAT-PCIAT_16
71  Parent-Child Internet Addiction Test     PCIAT-PCIAT_17
72  Parent-Child Internet Addiction Test     PCIAT-PCIAT_18
73  Parent-Child Internet Addiction Test     PCIAT-PCIAT_19
74  Parent-Child Internet Addiction Test     PCIAT-PCIAT_20
75  Parent-Child Internet Addiction Test  PCIAT-PCIAT_Total

                                          Description             Type
\
54                             Season of participation              str

55  How often does your child disobey time limits ...  categorical int

56  How often does your child neglect household ch...  categorical int

57  How often does your child prefer to spend time...  categorical int

58  How often does your child form new relationshi...  categorical int

59  How often do you complain about the amount of ...  categorical int

60  How often do your child's grades suffer becaus...  categorical int
```

```
61  How often does your child check his or her e-m...  categorical int

62  How often does your child seem withdrawn from ...  categorical int

63  How often does your child become defensive or ...  categorical int

64  How often have you caught your child sneaking ...  categorical int

65  How often does your child spend time along in ...  categorical int

66  How often does your child receive strange phon...  categorical int

67  How often does your child snap, yell, or act a...  categorical int

68  How often does your child seem more tired and ...  categorical int

69  How often does your child seem preoccupied wit...  categorical int

70  How often does your child throw tantrums with ...  categorical int

71  How often does your child choose to spend time...  categorical int

72  How often does your child become angry or bell...  categorical int

73  How often does your child choose to spend more...  categorical int

74  How often does your child feel depressed, mood...  categorical int

75                                        Total Score              int


                        Values  \
54  Spring, Summer, Fall, Winter
55                  0,1,2,3,4,5
56                  0,1,2,3,4,5
57                  0,1,2,3,4,5
58                  0,1,2,3,4,5
59                  0,1,2,3,4,5
60                  0,1,2,3,4,5
61                  0,1,2,3,4,5
62                  0,1,2,3,4,5
63                  0,1,2,3,4,5
64                  0,1,2,3,4,5
65                  0,1,2,3,4,5
66                  0,1,2,3,4,5
67                  0,1,2,3,4,5
68                  0,1,2,3,4,5
69                  0,1,2,3,4,5
70                  0,1,2,3,4,5
71                  0,1,2,3,4,5
72                  0,1,2,3,4,5
```

```
73                      0,1,2,3,4,5
74                      0,1,2,3,4,5
75                              NaN

                                                         Value Labels
54                                                                NaN
55  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
56  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
57  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
58  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
59  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
60  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
61  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
62  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
63  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
64  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
65  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
66  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
67  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
68  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
69  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
70  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
71  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
72  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
73  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
74  0=Does Not Apply, 1=Rarely, 2=Occasionally, 3=...
75  Severity Impairment Index: 0-30=None; 31-49=Mi...
```

Parent-Child Internet Addiction Test (PCIAT): contains 20 items (`PCIAT-PCIAT_01` to `PCIAT-PCIAT_20`), each assessing a different aspect of a child's behavior related to internet use. The items are answered on a scale (from 0 to 5), and the total score provides an indication of the severity of internet addiction.

We also have season of participation in `PCIAT-Season` and total Score in `PCIAT-PCIAT_Total`; so there are 22 PCIAT test-related columns in total.

Let's verify that the `PCIAT-PCIAT_Total` align with the corresponding sii categories by calculating its minimum and maximum scores for each sii category:

```
pciat_min_max = train.groupby('sii')['PCIAT-PCIAT_Total'].agg(['min',
'max'])
pciat_min_max = pciat_min_max.rename(
    columns={'min': 'Minimum PCIAT total Score', 'max': 'Maximum total
PCIAT Score'}
)
pciat_min_max

     Minimum PCIAT total Score  Maximum total PCIAT Score
sii
0.0                        0.0                       30.0
```

```
1.0                      31.0                      49.0
2.0                      50.0                      79.0
3.0                      80.0                      93.0
```

```
data_dict[data_dict['Field'] == 'PCIAT-PCIAT_Total']['Value Labels'].iloc[0]
```

```
'Severity Impairment Index: 0-30=None; 31-49=Mild; 50-79=Moderate; 80-100=Severe'
```

Check missing answers

```
train_with_sii = train[train['sii'].notna()][columns_not_in_test]
train_with_sii[train_with_sii.isna().any(axis=1)].head().style.applymap(
    lambda x: 'background-color: #FFC0CB' if pd.isna(x) else ''
)
```

```
<pandas.io.formats.style.Styler at 0x7e6c000c74f0>
```

For example, in the 1st and 3rd rows you can see that the score for one answer is missing. And since each question is scored from 1 to 5, the total score could be up to 5 points higher and correspond to the next SII category (SII can be 0 or 1 for the first row and 1 or 2 for the third). For the second row, `PCIAT-PCIAT_Total` and `sii` appears to have been filled in by mistake, as there are no test questions answered at all.

Let's check if PCIAT-PCIAT_Total was indeed calculated as a sum of non-NA values in `PCIAT-PCIAT_01` to `PCIAT-PCIAT_20` columns:

```
PCIAT_cols = [f'PCIAT-PCIAT_{i+1:02d}' for i in range(20)]
recalc_total_score = train_with_sii[PCIAT_cols].sum(
    axis=1, skipna=True
)
(recalc_total_score == train_with_sii['PCIAT-PCIAT_Total']).all()
```

```
True
```

For now, we can conclude that the SII score is sometimes incorrect. Below I recalculate the SII based on `PCIAT_Total` and the maximum possible score if missing values were answered (5 points), ensuring that the recalculated SII meets the intended thresholds even with some missing answers.

```
def recalculate_sii(row):
    if pd.isna(row['PCIAT-PCIAT_Total']):
        return np.nan
    max_possible = row['PCIAT-PCIAT_Total'] + row[PCIAT_cols].isna().sum() * 5
    if row['PCIAT-PCIAT_Total'] <= 30 and max_possible <= 30:
        return 0
```

```
    elif 31 <= row['PCIAT-PCIAT_Total'] <= 49 and max_possible <= 49:
        return 1
    elif 50 <= row['PCIAT-PCIAT_Total'] <= 79 and max_possible <= 79:
        return 2
    elif row['PCIAT-PCIAT_Total'] >= 80 and max_possible >= 80:
        return 3
    return np.nan

train['recalc_sii'] = train.apply(recalculate_sii, axis=1)
```

Verification of rows with different original and recalculated SII:

```
mismatch_rows = train[
    (train['recalc_sii'] != train['sii']) & train['sii'].notna()
]

mismatch_rows[PCIAT_cols + [
    'PCIAT-PCIAT_Total', 'sii', 'recalc_sii'
]].style.applymap(
    lambda x: 'background-color: #FFC0CB' if pd.isna(x) else ''
)
```

```
<pandas.io.formats.style.Styler at 0x7e6bfffa4820>
```

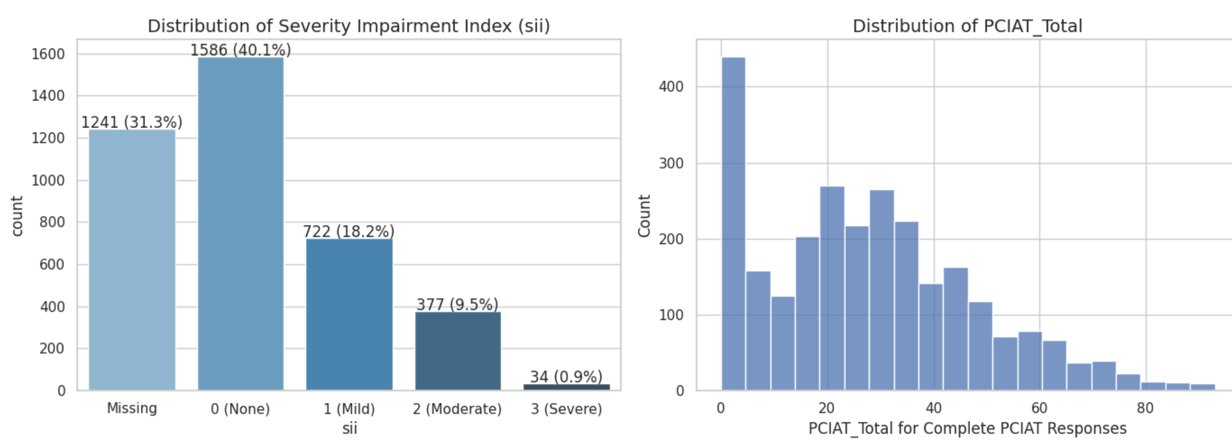
In the following analyses I'll only use the corrected SII. I will only use total scores if all PCIAT_cols have non-NA values (all questions of the Parent-Child Internet Addiction Test have been answered).

```
train['sii'] = train['recalc_sii']
train['complete_resp_total'] = train['PCIAT-PCIAT_Total'].where(
    train[PCIAT_cols].notna().all(axis=1), np.nan
)

sii_map = {0: '0 (None)', 1: '1 (Mild)', 2: '2 (Moderate)', 3: '3
(Severe)'}
train['sii'] = train['sii'].map(sii_map).fillna('Missing')

sii_order = ['Missing', '0 (None)', '1 (Mild)', '2 (Moderate)', '3
(Severe)']
train['sii'] = pd.Categorical(train['sii'], categories=sii_order,
ordered=True)

train.drop(columns='recalc_sii', inplace=True)
```

Plot distribution of the target variable

```
sii_counts = train['sii'].value_counts().reset_index()
total = sii_counts['count'].sum()
sii_counts['percentage'] = (sii_counts['count'] / total) * 100
```

```
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# SII
sns.barplot(x='sii', y='count', data=sii_counts, palette='Blues_d',
ax=axes[0])
axes[0].set_title('Distribution of Severity Impairment Index (sii)',
fontsize=14)
for p in axes[0].patches:
    height = p.get_height()
    percentage = sii_counts.loc[sii_counts['count'] == height,
'percentage'].values[0]
    axes[0].text(
        p.get_x() + p.get_width() / 2,
        height + 5, f'{int(height)} ({percentage:.1f}%)',
        ha="center", fontsize=12
    )

# PCIAT_Total for complete responses
sns.histplot(train['complete_resp_total'].dropna(), bins=20,
ax=axes[1])
axes[1].set_title('Distribution of PCIAT_Total', fontsize=14)
axes[1].set_xlabel('PCIAT_Total for Complete PCIAT Responses')

plt.tight_layout()
plt.show()
```




```
len(train[train['complete_resp_total'] == 0])
```

```
307
```

SII by age and sex

```
assert train['Basic_Demos-Age'].isna().sum() == 0
assert train['Basic_Demos-Sex'].isna().sum() == 0
```

```python
train['Age Group'] = pd.cut(
    train['Basic_Demos-Age'],
    bins=[4, 12, 18, 22],
    labels=['Children (5-12)', 'Adolescents (13-18)', 'Adults (19-
22)']
)
calculate_stats(train, 'Age Group')
```

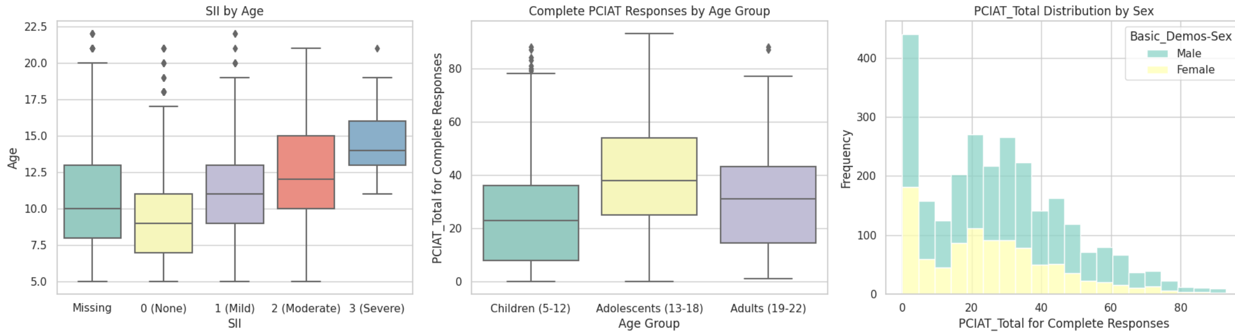
```
                         count (%)
Age Group
Children (5-12)      2919 (73.71%)
Adolescents (13-18)   953 (24.07%)
Adults (19-22)         88 (2.22%)
```

```python
sex_map = {0: 'Male', 1: 'Female'}
train['Basic_Demos-Sex'] = train['Basic_Demos-Sex'].map(sex_map)
calculate_stats(train, 'Basic_Demos-Sex')
```

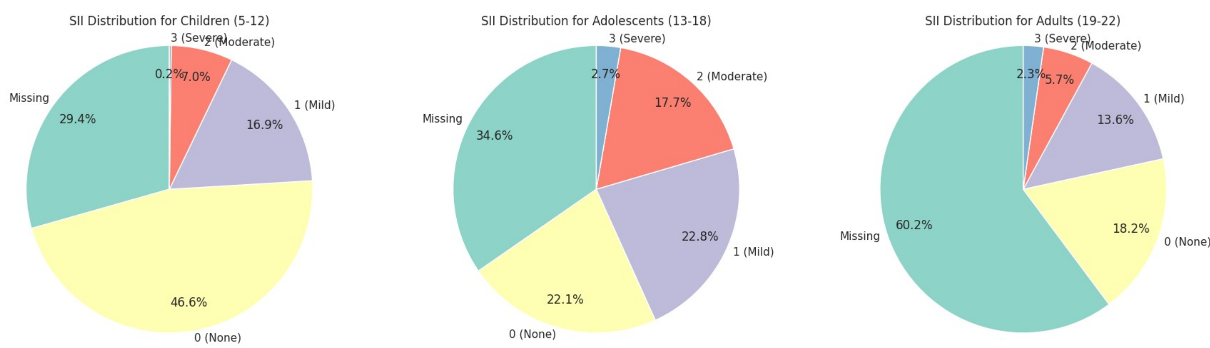
```
                     count (%)
Basic_Demos-Sex
Male             2484 (62.73%)
Female           1476 (37.27%)
```

```python
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

# SII by Age
sns.boxplot(y=train['Basic_Demos-Age'], x=train['sii'], ax=axes[0],
palette="Set3")
axes[0].set_title('SII by Age')
axes[0].set_ylabel('Age')
axes[0].set_xlabel('SII')

# Complete PCIAT Responses by Age Group
sns.boxplot(
    x='Age Group', y='complete_resp_total',
    data=train, palette="Set3", ax=axes[1]
)
axes[1].set_title('Complete PCIAT Responses by Age Group')
axes[1].set_ylabel('PCIAT_Total for Complete Responses')
axes[1].set_xlabel('Age Group')

# PCIAT_Total by Sex
sns.histplot(
    data=train, x='complete_resp_total',
    hue='Basic_Demos-Sex', multiple='stack',
    palette="Set3", bins=20, ax=axes[2]
)
axes[2].set_title('PCIAT_Total Distribution by Sex')
axes[2].set_xlabel('PCIAT_Total for Complete Responses')
axes[2].set_ylabel('Frequency')
```

```
plt.tight_layout()
plt.show()
```




```
stats = train.groupby(['Age Group',
'sii']).size().unstack(fill_value=0)
fig, axes = plt.subplots(1, len(stats), figsize=(18, 5))

for i, age_group in enumerate(stats.index):
    group_counts = stats.loc[age_group] / stats.loc[age_group].sum()
    axes[i].pie(
        group_counts, labels=group_counts.index, autopct='%1.1f%%',
        startangle=90, colors=sns.color_palette("Set3"),
        labeldistance=1.05, pctdistance=0.80
    )
    axes[i].set_title(f'SII Distribution for {age_group}')
    axes[i].axis('equal')

plt.tight_layout()
plt.show()
```



The distribution of sii across different age groups:

```
stats = train.groupby(['Age Group',
'sii']).size().unstack(fill_value=0)
stats_prop = stats.div(stats.sum(axis=1), axis=0) * 100

stats = stats.astype(str) +' (' + stats_prop.round(1).astype(str) +
```

```
'%)'
stats

sii                           Missing      0 (None)     1 (Mild) 2
(Moderate)  \
Age Group

Children (5-12)       858 (29.4%)  1359 (46.6%)  493 (16.9%)   203
(7.0%)
Adolescents (13-18)  330 (34.6%)   211 (22.1%)  217 (22.8%)  169
(17.7%)
Adults (19-22)         53 (60.2%)    16 (18.2%)   12 (13.6%)     5
(5.7%)

sii                    3 (Severe)
Age Group
Children (5-12)         6 (0.2%)
Adolescents (13-18)   26 (2.7%)
Adults (19-22)          2 (2.3%)
```

Calculate percentages for participants with non-missing SII only:

```
stats = train[train['sii'] != 'Missing'].groupby(
    ['Age Group', 'sii']
).size().unstack(fill_value=0)
stats_prop = stats.div(stats.sum(axis=1), axis=0) * 100

stats = stats.astype(str) +' (' + stats_prop.round(1).astype(str) +
'%)'
stats

sii                       Missing      0 (None)     1 (Mild) 2 (Moderate)
\
Age Group

Children (5-12)       0 (0.0%)  1359 (65.9%)  493 (23.9%)   203 (9.8%)

Adolescents (13-18)  0 (0.0%)   211 (33.9%)  217 (34.8%)  169 (27.1%)

Adults (19-22)        0 (0.0%)    16 (45.7%)   12 (34.3%)     5 (14.3%)


sii                    3 (Severe)
Age Group
Children (5-12)         6 (0.3%)
Adolescents (13-18)   26 (4.2%)
Adults (19-22)          2 (5.7%)
```

Internet Use

Internet usage data is crucial to this task because Problematic internet use (PIU), also known as internet addiction or compulsive internet use, refers to excessive and unhealthy use of the internet that interferes with a person's daily life, responsibilities, and social relationships. The internet usage data provides a direct measure of how much time each participant spends online.

```
data = train[train['PreInt_EduHx-computerinternet_hoursday'].notna()]
age_range = data['Basic_Demos-Age']
print(
    f"Age range for participants with measured PreInt_EduHx-
computerinternet_hoursday data:"
    f" {age_range.min()} - {age_range.max()} years"
)
```

```
Age range for participants with measured PreInt_EduHx-
computerinternet_hoursday data: 5 - 22 years
```

```
train['PreInt_EduHx-computerinternet_hoursday'].unique()
```

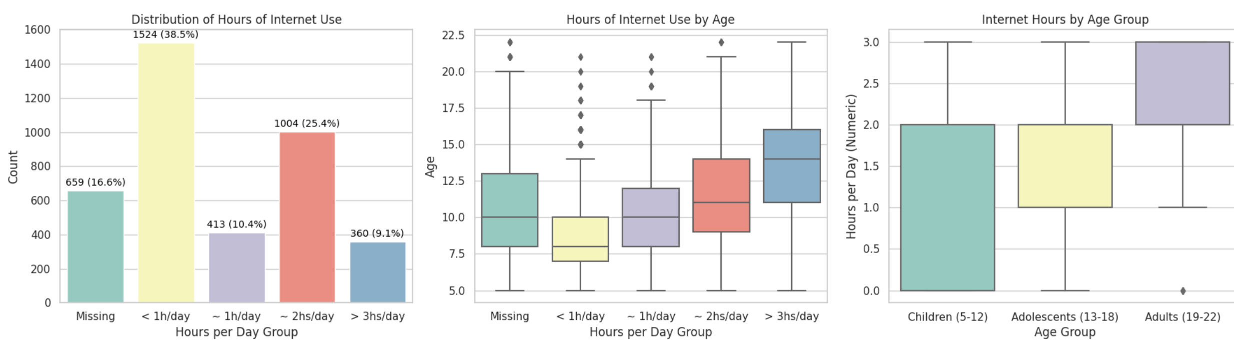
```
array([ 3.,  0.,  2., nan,  1.])
```

```
param_map = {0: '< 1h/day', 1: '~ 1h/day', 2: '~ 2hs/day', 3: '>
3hs/day'}
train['internet_use_encoded'] = train[
    'PreInt_EduHx-computerinternet_hoursday'
].map(param_map).fillna('Missing')

param_ord = ['Missing', '< 1h/day', '~ 1h/day', '~ 2hs/day', '>
3hs/day']
train['internet_use_encoded'] = pd.Categorical(
    train['internet_use_encoded'], categories=param_ord,
    ordered=True
)

calculate_stats(train, 'PreInt_EduHx-Season')
```

PreInt_EduHx-Season	count (%)
Fall	828 (20.91%)
Summer	821 (20.73%)
Winter	906 (22.88%)
NaN	420 (10.61%)
Spring	985 (24.87%)

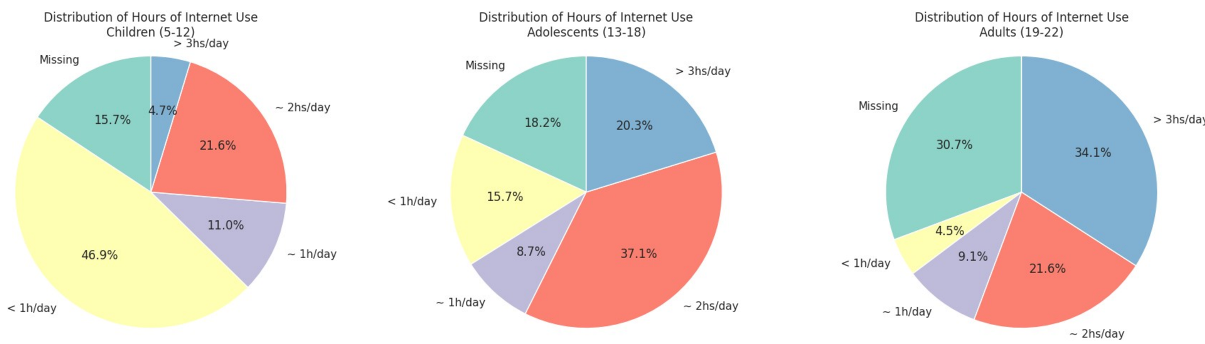
```
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

# Hours of Internet Use
ax1 = sns.countplot(x='internet_use_encoded', data=train,
palette="Set3", ax=axes[0])
```

```
axes[0].set_title('Distribution of Hours of Internet Use')
axes[0].set_xlabel('Hours per Day Group')
axes[0].set_ylabel('Count')

total = len(train['internet_use_encoded'])
for p in ax1.patches:
    count = int(p.get_height())
    percentage = '{:.1f}%'.format(100 * count / total)
    ax1.annotate(f'{count} ({percentage})', (p.get_x() + p.get_width()
/ 2., p.get_height()),
                 ha='center', va='baseline', fontsize=10,
color='black', xytext=(0, 5),
                 textcoords='offset points')

# Hours of Internet Use by Age
sns.boxplot(y=train['Basic_Demos-Age'],
x=train['internet_use_encoded'], ax=axes[1], palette="Set3")
axes[1].set_title('Hours of Internet Use by Age')
axes[1].set_ylabel('Age')
axes[1].set_xlabel('Hours per Day Group')

# Hours of Internet Use (numeric) by Age Group
sns.boxplot(y='PreInt_EduHx-computerinternet_hoursday', x='Age Group',
data=train, ax=axes[2], palette="Set3")
axes[2].set_title('Internet Hours by Age Group')
axes[2].set_ylabel('Hours per Day (Numeric)')
axes[2].set_xlabel('Age Group')

plt.tight_layout()
plt.show()
```




```
stats = train.groupby(
    ['Age Group', 'internet_use_encoded']
).size().unstack(fill_value=0)
fig, axes = plt.subplots(1, len(stats), figsize=(18, 5))

for i, age_group in enumerate(stats.index):
    group_counts = stats.loc[age_group] / stats.loc[age_group].sum()
    axes[i].pie(group_counts, labels=group_counts.index,
```

```
autopct='%1.1f%%',
                startangle=90, colors=sns.color_palette("Set3"),
labeldistance=1.1)
    axes[i].set_title(f'Distribution of Hours of Internet Use\
n{age_group}')
    axes[i].axis('equal')

plt.tight_layout()
plt.show()
```




```
train_non_na = train.dropna(subset=['PreInt_EduHx-
computerinternet_hoursday'])
rows = (train_non_na['PreInt_EduHx-computerinternet_hoursday'] ==
3).sum()
print(f"Non-NA Rows - Internet use 3h or more: {(rows /
len(train_non_na)) * 100:.2f}%")

rows = (train_non_na['PreInt_EduHx-computerinternet_hoursday'] ==
0).sum()
print(f"Non-NA Rows - Internet use 1h or less: {(rows /
len(train_non_na)) * 100:.2f}%")

Non-NA Rows - Internet use 3h or more: 10.91%
Non-NA Rows - Internet use 1h or less: 46.17%

stats = train.groupby(['Basic_Demos-Sex', 'internet_use_encoded']
).size().unstack(fill_value=0)
stats_prop = stats.div(stats.sum(axis=1), axis=0) * 100

stats = stats.astype(str) +' (' + stats_prop.round(1).astype(str) +
'%)'
stats

internet_use_encoded      Missing     < 1h/day     ~ 1h/day    ~
2hs/day  \
Basic_Demos-Sex

Female                 271 (18.4%)  569 (38.6%)   139 (9.4%)  353
(23.9%)
```

```
Male                          388 (15.6%)  955 (38.4%)  274 (11.0%)  651
(26.2%)

internet_use_encoded    > 3hs/day
Basic_Demos-Sex
Female                  144 (9.8%)
Male                    216 (8.7%)
```

Internet usage vs SII (target)

Competition description states that the goal is: to detect early indicators of problematic Internet and technology use (PIU), while the definition of PUI includes excessive use of internet:

> PUI is an umbrella term that encompasses a set of potentially harmful online behaviors that are repetitive and uncontrolled, to the point that they are prioritized over other life interests and persist despite negative consequences.

Fendel, J. C., Vogt, A., Brandtner, A., & Schmidt, S. (2024). Mindfulness programs for problematic usage of the internet: A systematic review and meta-analysis. Journal of behavioral addictions, 13(2), 327–353.

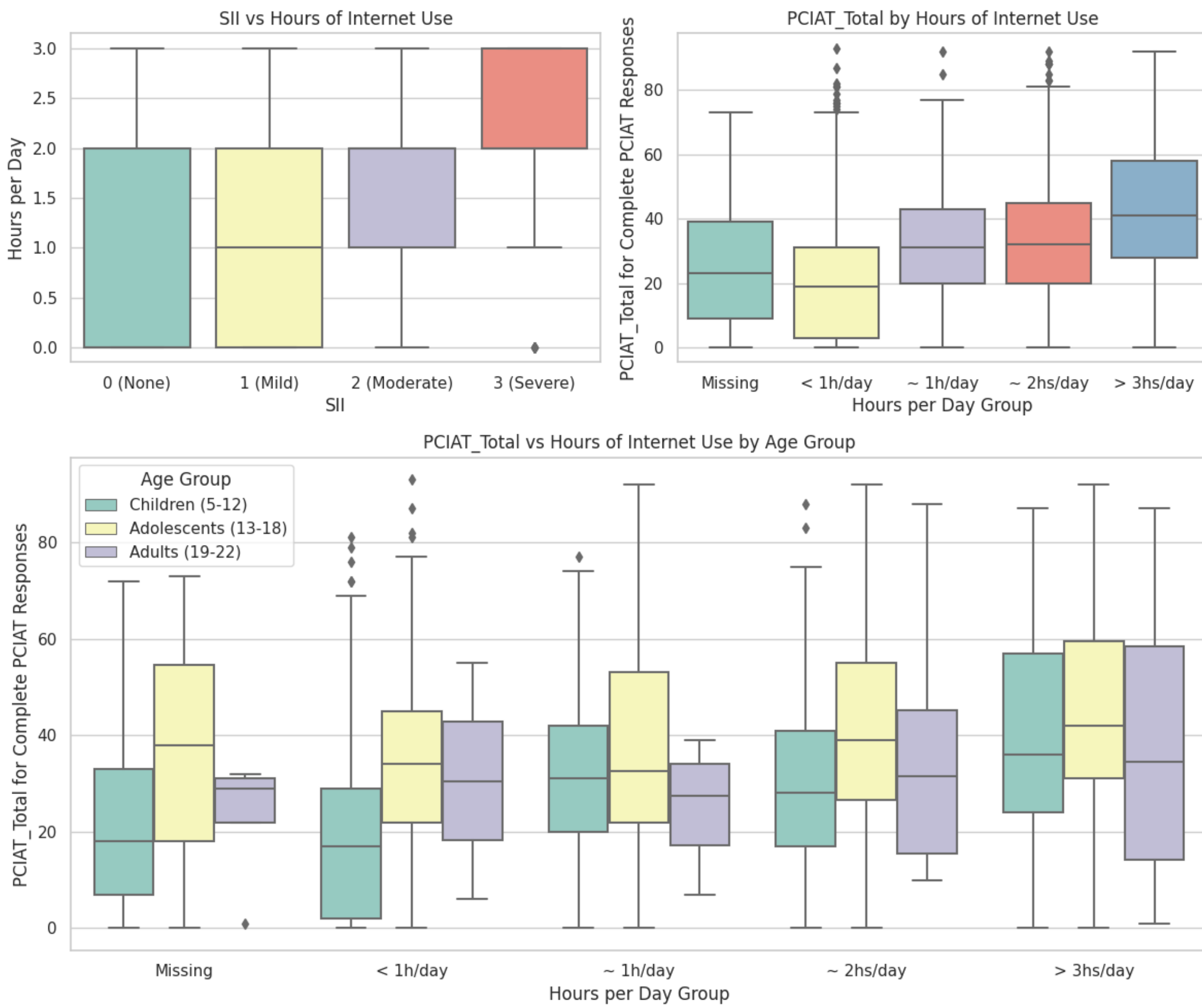
So let's see how much time the participants with different impairment scores (SII) spent online in this dataset.

```
sii_reported = train[train['sii'] != "Missing"]
sii_reported.loc[:, 'sii'] =
sii_reported['sii'].cat.remove_unused_categories()

stats = sii_reported.groupby(
    ['internet_use_encoded', 'sii']
).size().unstack(fill_value=0)
stats_prop = stats.div(stats.sum(axis=1), axis=0) * 100

stats = stats.astype(str) +' (' + stats_prop.round(1).astype(str) +
'%)'
stats
```

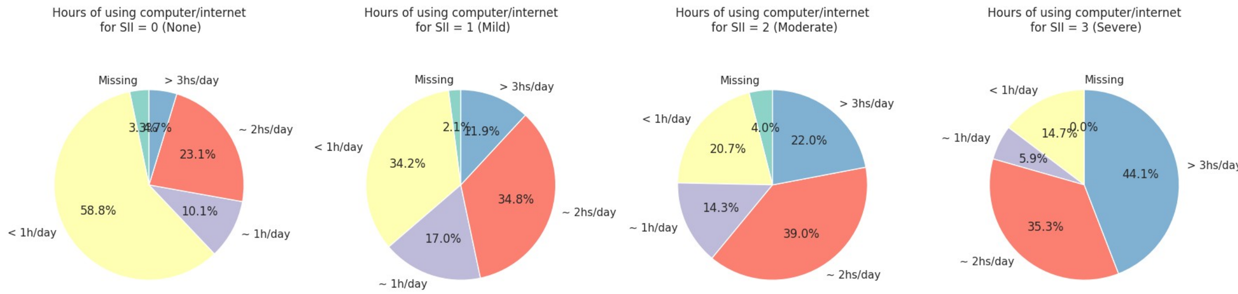
```
sii                         0 (None)     1 (Mild) 2 (Moderate) 3 (Severe)
internet_use_encoded
Missing                   52 (63.4%)   15 (18.3%)   15 (18.3%)   0 (0.0%)
< 1h/day                 933 (73.9%)  247 (19.6%)    78 (6.2%)   5 (0.4%)
~ 1h/day                 160 (47.2%)  123 (36.3%)   54 (15.9%)   2 (0.6%)
~ 2hs/day                366 (47.2%)  251 (32.3%)  147 (18.9%)  12 (1.5%)
> 3hs/day                 75 (29.0%)   86 (33.2%)   83 (32.0%)  15 (5.8%)
```

```
fig = plt.figure(figsize=(12, 10))
gs = fig.add_gridspec(2, 2, height_ratios=[1, 1.5])

# SII vs Hours of Internet Use
ax1 = fig.add_subplot(gs[0, 0])
```

```python
sns.boxplot(
    x='sii', y='PreInt_EduHx-computerinternet_hoursday',
    data=sii_reported,
    ax=ax1, palette="Set3"
)
ax1.set_title('SII vs Hours of Internet Use')
ax1.set_ylabel('Hours per Day')
ax1.set_xlabel('SII')

# PCIAT_Total for Complete PCIAT Responses by Hours of Internet Use
ax2 = fig.add_subplot(gs[0, 1])
sns.boxplot(
    x='internet_use_encoded', y='complete_resp_total',
    data=sii_reported,
    palette="Set3", ax=ax2
)
ax2.set_title('PCIAT_Total by Hours of Internet Use')
ax2.set_ylabel('PCIAT_Total for Complete PCIAT Responses')
ax2.set_xlabel('Hours per Day Group')

# SII vs Hours of Internet Use by Age Group (Full width)
ax3 = fig.add_subplot(gs[1, :])
sns.boxplot(
    x='internet_use_encoded', y='complete_resp_total',
    data=sii_reported,
    hue='Age Group', ax=ax3, palette="Set3"
)
ax3.set_title('PCIAT_Total vs Hours of Internet Use by Age Group')
ax3.set_ylabel('PCIAT_Total for Complete PCIAT Responses')
ax3.set_xlabel('Hours per Day Group')

plt.tight_layout()
plt.show()
```




```
stats = sii_reported.groupby(
    ['sii', 'internet_use_encoded']
).size().unstack(fill_value=0)
fig, axes = plt.subplots(1, len(stats), figsize=(18, 5))

for i, sii_group in enumerate(stats.index):
    group_counts = stats.loc[sii_group] / stats.loc[sii_group].sum()
    axes[i].pie(
        group_counts, labels=group_counts.index, autopct='%1.1f%%',
        startangle=90, colors=sns.color_palette("Set3"),
labeldistance=1.1
    )
    axes[i].set_title(f'Hours of using computer/internet\n for SII =
{sii_group}')
    axes[i].axis('equal')

plt.tight_layout()
plt.show()
```




```
stats = sii_reported.groupby(
    ['sii', 'internet_use_encoded']
).size().unstack(fill_value=0)
stats_prop = stats.div(stats.sum(axis=1), axis=0) * 100

stats = stats.astype(str) +' (' + stats_prop.round(1).astype(str) +
'%)'
stats
```

```
internet_use_encoded    Missing     < 1h/day     ~ 1h/day    ~ 2hs/day
\
sii

0 (None)               52 (3.3%)  933 (58.8%)  160 (10.1%)  366 (23.1%)

1 (Mild)               15 (2.1%)  247 (34.2%)  123 (17.0%)  251 (34.8%)

2 (Moderate)           15 (4.0%)   78 (20.7%)   54 (14.3%)  147 (39.0%)

3 (Severe)              0 (0.0%)    5 (14.7%)     2 (5.9%)   12 (35.3%)


internet_use_encoded   > 3hs/day
sii
0 (None)                75 (4.7%)
1 (Mild)               86 (11.9%)
2 (Moderate)           83 (22.0%)
3 (Severe)             15 (44.1%)
```

```
train[
    (train['internet_use_encoded'] == '< 1h/day') &
    (train['sii'].isin(['2 (Moderate)', '3 (Severe)']))
]['Basic_Demos-Age'].describe()
```

```
count    83.000000
mean     10.626506
std       3.083041
min       5.000000
25%       8.500000
50%      10.000000
```

```
75%        12.500000
max        21.000000
Name: Basic_Demos-Age, dtype: float64
```

Features EDA by Groups

Here's how we can classify types of the features in this dataset:

- Categorical: Variables with discrete categories but no inherent order (represented as strings, e.g., season of enrollment)
- Encoded categorical features (already encoded as integers, e.g. sex)
- Continuous: Variables that can take any value within a range (e.g., age, enmo, heart_rate).
- Ordinal: Variables with a defined order but not necessarily equidistant categories (e.g., questionnaire responses).

And here are different features groups:

```python
groups = data_dict.groupby('Instrument')
['Field'].apply(list).to_dict()

for instrument, features in groups.items():
    print(f"{instrument}: {features}\n")
```

```
Bio-electric Impedance Analysis: ['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']

Children's Global Assessment Scale: ['CGAS-Season', 'CGAS-CGAS_Score']

Demographics: ['Basic_Demos-Enroll_Season', 'Basic_Demos-Age',
'Basic_Demos-Sex']

FitnessGram Child: ['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']

FitnessGram Vitals and Treadmill: ['Fitness_Endurance-Season',
'Fitness_Endurance-Max_Stage', 'Fitness_Endurance-Time_Mins',
'Fitness_Endurance-Time_Sec']

Identifier: ['id']

Internet Use: ['PreInt_EduHx-Season', 'PreInt_EduHx-
```

```
computerinternet_hoursday']

Parent-Child Internet Addiction Test: ['PCIAT-Season', 'PCIAT-PCIAT_01', 'PCIAT-PCIAT_02', 'PCIAT-PCIAT_03', 'PCIAT-PCIAT_04', 'PCIAT-PCIAT_05', 'PCIAT-PCIAT_06', 'PCIAT-PCIAT_07', 'PCIAT-PCIAT_08', 'PCIAT-PCIAT_09', 'PCIAT-PCIAT_10', 'PCIAT-PCIAT_11', 'PCIAT-PCIAT_12', 'PCIAT-PCIAT_13', 'PCIAT-PCIAT_14', 'PCIAT-PCIAT_15', 'PCIAT-PCIAT_16', 'PCIAT-PCIAT_17', 'PCIAT-PCIAT_18', 'PCIAT-PCIAT_19', 'PCIAT-PCIAT_20', 'PCIAT-PCIAT_Total']

Physical Activity Questionnaire (Adolescents): ['PAQ_A-Season', 'PAQ_A-PAQ_A_Total']

Physical Activity Questionnaire (Children): ['PAQ_C-Season', 'PAQ_C-PAQ_C_Total']

Physical Measures: ['Physical-Season', 'Physical-BMI', 'Physical-Height', 'Physical-Weight', 'Physical-Waist_Circumference', 'Physical-Diastolic_BP', 'Physical-HeartRate', 'Physical-Systolic_BP']

Sleep Disturbance Scale: ['SDS-Season', 'SDS-SDS_Total_Raw', 'SDS-SDS_Total_T']
```

Season-related columns

The presence of different season-related columns likely reflects the timing of data collection or participation in the study. Seasonal changes may play a significant role in the variables being measured (e.g., fitness, physical activity, sleep patterns, and of course internet usage).

```
season_columns = [col for col in train.columns if 'Season' in col]
season_df = train[season_columns]
season_df
```

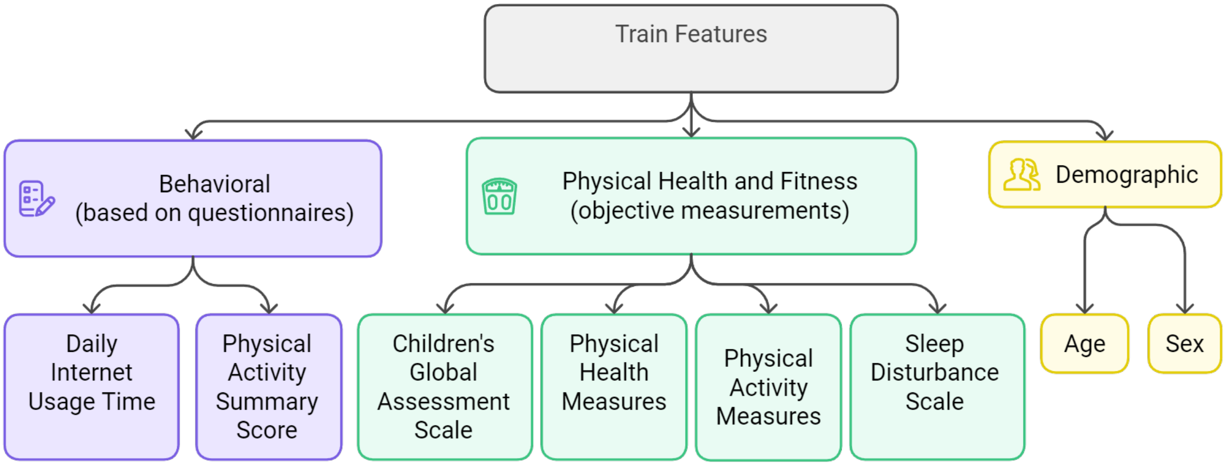
```
     Basic_Demos-Enroll_Season CGAS-Season Physical-Season  \
0                         Fall      Winter            Fall
1                       Summer         NaN            Fall
2                       Summer        Fall            Fall
3                       Winter        Fall          Summer
4                       Spring      Summer             NaN
...                        ...         ...             ...
3955                      Fall      Spring            Fall
3956                    Winter         NaN          Spring
3957                      Fall      Spring          Winter
3958                    Spring      Spring          Winter
3959                    Spring         NaN          Winter

     Fitness_Endurance-Season FGC-Season BIA-Season PAQ_A-Season
PAQ_C-Season  \
0                         NaN       Fall       Fall          NaN
```

```
NaN
1                          NaN        Fall      Winter             NaN
Fall
2                         Fall        Fall         NaN             NaN
Summer
3                       Summer      Summer      Summer             NaN
Winter
4                          NaN         NaN         NaN          Summer
NaN
...                        ...         ...         ...             ...
...
3955                       NaN        Fall        Fall             NaN
Winter
3956                       NaN      Spring      Spring             NaN
Winter
3957                       NaN      Winter      Winter             NaN
Winter
3958                       NaN      Spring      Summer             NaN
Spring
3959                       NaN      Winter         NaN             NaN
NaN

     PCIAT-Season SDS-Season PreInt_EduHx-Season
0            Fall        NaN                Fall
1            Fall       Fall              Summer
2            Fall       Fall              Summer
3          Summer     Summer              Winter
4             NaN        NaN                 NaN
...           ...        ...                 ...
3955       Winter     Winter                Fall
3956          NaN        NaN              Winter
3957       Winter     Winter                Fall
3958       Spring     Spring              Spring
3959          NaN        NaN              Spring

[3960 rows x 11 columns]
```

```
train[season_columns] = train[season_columns].fillna("Missing")
```

Grouping of features by type and measurement method

Having examined the contents of data_dict in detail, I believe that the characteristics can also be grouped according to their type and method of measurement (the diagram was made with napkin):



Potential connection to problematic internet use (PIU)

- Behavioral (subjective reported):
  - A person can't have PIU if they don't use the internet, so I would expect `PreInt_EduHx-computerinternet_hoursday` to be the most important feature, but as we saw above, its relationship with the target can be non-linear.
  - Behavioural tendencies associated with PIU may be reflected in the physical activity score derived from the questionnaires (`PAQ_A-PAQ_A_Total` and `PAQ_C-PAQ_C_Total`).

  However, both features are self-reports and are likely to be biased and inaccurate, so I would expect noise here.

- Physical Health and Fitness (objective measurements):
  - The Children's Global Assessment Scale (`CGAS-CGAS_Score`) is a clinician-rated score reflecting general functioning. For individuals with PIU, this score can indicate how PIU impacts overall functioning.
  - Physical health measures include body composition and vital signs (feature columns starting with `Physical-`), and may reflect how problematic internet use is in terms of its impact on general health (note that height alone may not be as relevant, but combined with weight it gives BMI - a measure of body fat).
  - Bio-electric Impedance Analysis assess body composition and metabolic health (body fat, muscle mass, water content, metabolic rate, etc.), PIU, if assosiated with sedentary behavior could be reflected through changes in these variables (lower bone density, lower lean muscle mass, reduced daily energy expenditure, poor hydration, decrease in fat-free mass, higher body fat percentages, and so on).
  - Objective measures of physical activity include FitnessGram results (endurance, curl, grip, push-up, sit & reach, trunk lift - feature columns starting with `Fitness_` and `FGC-FGC_`). These can indicate how problematic internet use is in terms of its impact on muscle strength and tonus.

- An assessment of sleep-related issues (feature columns `SDS-SDS_Total_Raw`, `SDS-SDS_Total_T`) could reflect the extent to which PIU disrupts sleep patterns.

- Demographic features:
  - Age and gender can be extremely important, as there may be gender and especially age-specific patterns (as we have already seen above) associated with Internet use and PIU)

Remove target-related columns and continue EDA by feature groups.

```
data_dict = data_dict[data_dict['Instrument'] != 'Parent-Child
Internet Addiction Test']
continuous_cols = data_dict[data_dict['Type'].str.contains(
    'float|int', case=False
)]['Field'].tolist()

# target = train[['sii']]
# train = train.drop(columns = columns_not_in_test)
```

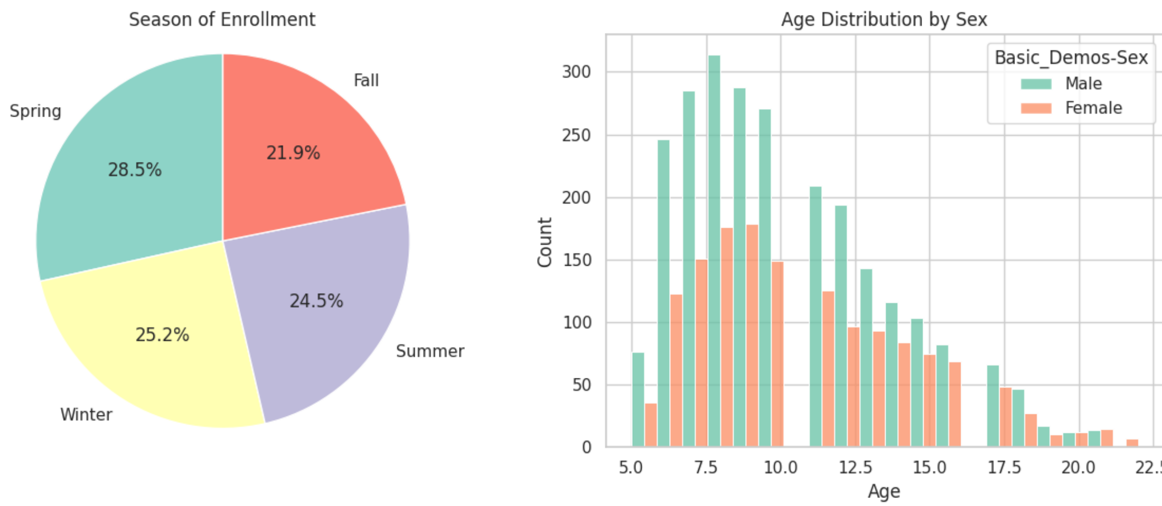
- Demographics

```
groups.get('Demographics', [])
```

```
['Basic_Demos-Enroll_Season', 'Basic_Demos-Age', 'Basic_Demos-Sex']
```

```
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Season of Enrollment
season_counts = train['Basic_Demos-
Enroll_Season'].value_counts(dropna=False)

axes[0].pie(
    season_counts, labels=season_counts.index,
    autopct='%1.1f%%', startangle=90,
    colors=sns.color_palette("Set3")
)
axes[0].set_title('Season of Enrollment')
axes[0].axis('equal')

# Age Distribution by Sex
sns.histplot(
    data=train, x='Basic_Demos-Age',
    hue='Basic_Demos-Sex', multiple='dodge',
    palette="Set2", bins=20, ax=axes[1]
)
axes[1].set_title('Age Distribution by Sex')
axes[1].set_xlabel('Age')
axes[1].set_ylabel('Count')
```

```
plt.tight_layout()
plt.show()
```



0=Male, 1=Female

```
calculate_stats(train, 'Basic_Demos-Age')
```

```
                  count       mean       std  min  25%   50%   75%  
max  \
Basic_Demos-Age                                                      

Basic_Demos-Age  3960.0  10.433586  3.574648  5.0  8.0  10.0  13.0  
22.0   

                 missing  
Basic_Demos-Age           
Basic_Demos-Age        0  
```

Physical Health and Fitness (objective measurements)

- Children's Global Assessment Scale

```
groups.get("Children's Global Assessment Scale", [])
```

```
['CGAS-Season', 'CGAS-CGAS_Score']
```

```python
data = train[train['CGAS-CGAS_Score'].notnull()]
age_range = data['Basic_Demos-Age']
print(
    f"Age range for participants with CGAS-CGAS_Score data:"
    f" {age_range.min()} - {age_range.max()} years"
)
```

```
Age range for participants with CGAS-CGAS_Score data: 5 - 22 years
```

```python
calculate_stats(train, 'CGAS-CGAS_Score')
```

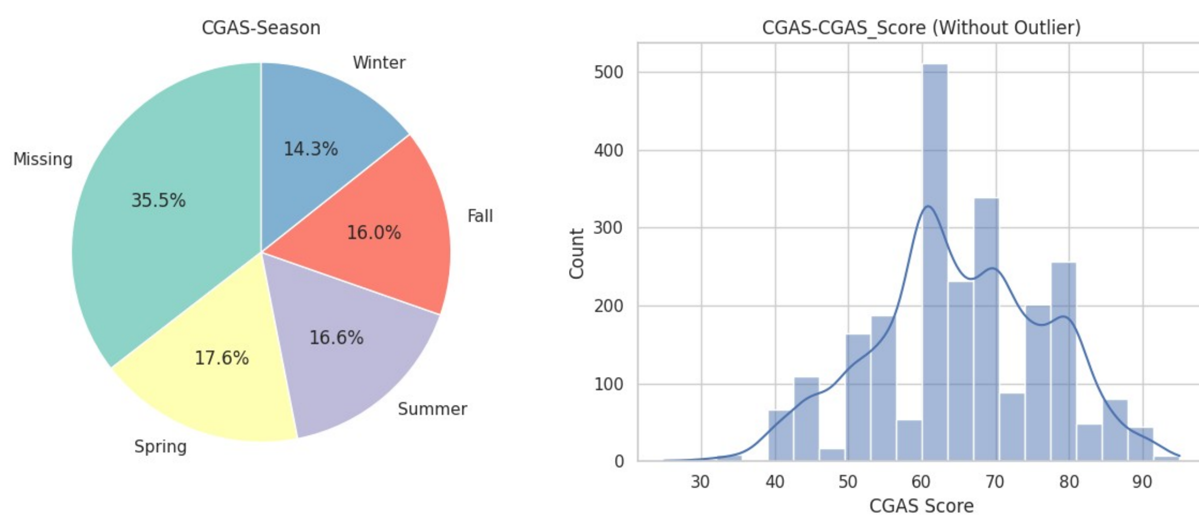
```
                  count       mean        std   min   25%   50%   75%
max  \
CGAS-CGAS_Score

CGAS-CGAS_Score  2421.0  65.454771  22.341862  25.0  59.0  65.0  75.0
999.0

                 missing
CGAS-CGAS_Score
CGAS-CGAS_Score     1539
```

```python
train[train['CGAS-CGAS_Score'] > 100]
```

```
            id Basic_Demos-Enroll_Season  Basic_Demos-Age Basic_Demos-
Sex  \
2065  83525bbe                      Fall               11
Female

     CGAS-Season  CGAS-CGAS_Score Physical-Season  Physical-BMI  \
2065      Winter            999.0            Fall           NaN

      Physical-Height  Physical-Weight  ...  PCIAT-PCIAT_Total  SDS-
Season  \
2065              NaN              NaN  ...                NaN
Missing

      SDS-SDS_Total_Raw  SDS-SDS_Total_T PreInt_EduHx-Season  \
2065                NaN              NaN                Fall

      PreInt_EduHx-computerinternet_hoursday      sii
complete_resp_total  \
2065                                    3.0  Missing
NaN

            Age Group  internet_use_encoded
2065  Children (5-12)             > 3hs/day

[1 rows x 85 columns]
```

```python
train.loc[train['CGAS-CGAS_Score'] == 999, 'CGAS-CGAS_Score'] = np.nan
```

```
plt.figure(figsize=(12, 5))

# CGAS-Season
plt.subplot(1, 2, 1)
cgas_season_counts = train['CGAS-Season'].value_counts(normalize=True)
plt.pie(
    cgas_season_counts,
    labels=cgas_season_counts.index,
    autopct='%1.1f%%',
    startangle=90,
    colors=sns.color_palette("Set3")
)
plt.title('CGAS-Season')
plt.axis('equal')

# CGAS-CGAS_Score without outliers (score == 999)
plt.subplot(1, 2, 2)
sns.histplot(
    train['CGAS-CGAS_Score'].dropna(),
    bins=20, kde=True
)
plt.title('CGAS-CGAS_Score (Without Outlier)')
plt.xlabel('CGAS Score')
plt.ylabel('Count')

plt.tight_layout()
plt.show()
```



Stats without outlier:

```
calculate_stats(train, 'CGAS-CGAS_Score')
```

```
                    count        mean         std    min    25%    50%    75%
max  \
```

```
CGAS-CGAS_Score

CGAS-CGAS_Score  2420.0  65.069008  11.78731  25.0  59.0  65.0  75.0
95.0

                    missing
CGAS-CGAS_Score
CGAS-CGAS_Score     1540
```

CGAS Interpretation (Reference)

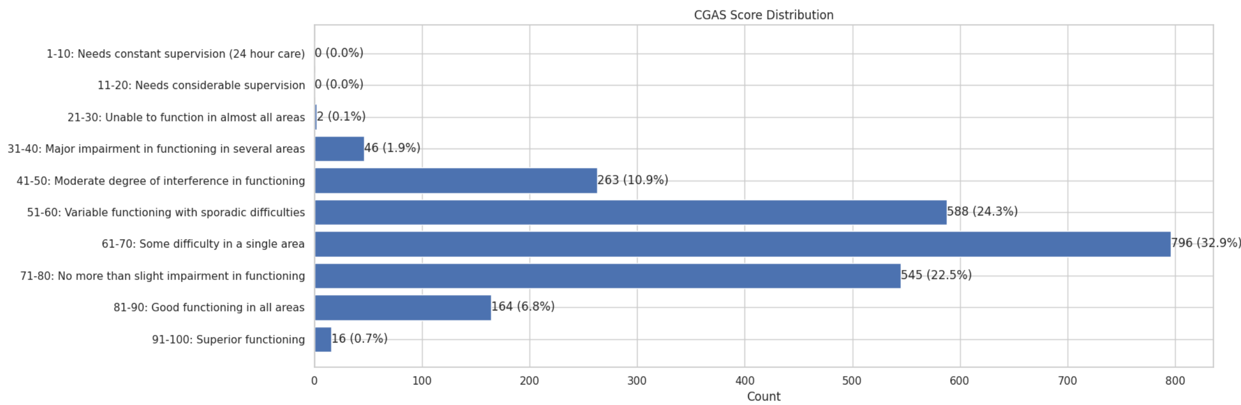
CGAS is a rating of general functioning for children and young people aged 4-16 years old. The CGAS asks the clinician to rate the child from 1 to 100 based on their lowest level of functioning, regardless of treatment or prognosis, over a specified time period.

Since the CGAS is a measure of general functioning, and the SII reflects the severity of the impact of Internet use on that functioning, I expect this feature, along with Internet use, to be the most important in predicting the SII.

Let's bin the `CGAS-CGAS_Score` column based on the established score categories and draw counts:

```
bins = np.arange(0, 101, 10)
labels = [
    "1-10: Needs constant supervision (24 hour care)",
    "11-20: Needs considerable supervision",
    "21-30: Unable to function in almost all areas",
    "31-40: Major impairment in functioning in several areas",
    "41-50: Moderate degree of interference in functioning",
    "51-60: Variable functioning with sporadic difficulties",
    "61-70: Some difficulty in a single area",
    "71-80: No more than slight impairment in functioning",
    "81-90: Good functioning in all areas",
    "91-100: Superior functioning"
]

train['CGAS_Score_Bin'] = pd.cut(
    train['CGAS-CGAS_Score'], bins=bins, labels=labels
)

counts = train['CGAS_Score_Bin'].value_counts().reindex(labels)
prop = (counts / counts.sum() * 100).round(1)
count_prop_labels = counts.astype(str) + " (" + prop.astype(str) +
"%)"

plt.figure(figsize=(18, 6))
bars = plt.barh(labels, counts)
plt.xlabel('Count')
plt.title('CGAS Score Distribution')
```

```
for bar, label in zip(bars, count_prop_labels):
    plt.text(
        bar.get_width(), bar.get_y() + bar.get_height() / 2, label,
va='center'
    )

plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```



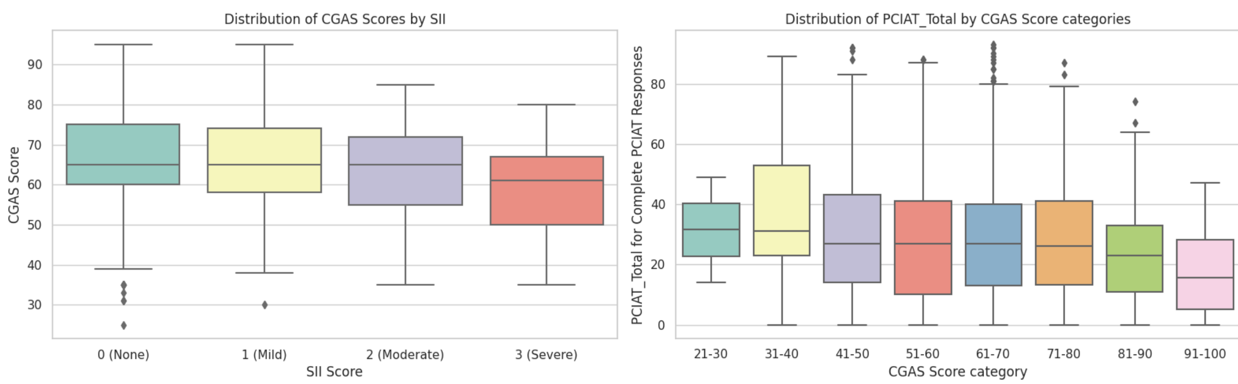
Examine relationships with the target variable:

```
train_filt = train.dropna(subset=['CGAS_Score_Bin',
'complete_resp_total'])
train_filt.loc[:, 'CGAS_Score_Bin'] =
train_filt['CGAS_Score_Bin'].cat.remove_unused_categories()
train_filt.loc[:, 'sii'] =
train_filt['sii'].cat.remove_unused_categories()
len(train_filt)
```

```
2288
```

```
fig, axes = plt.subplots(1, 2, figsize=(16, 5))

# CGAS-CGAS_Score vs sii
sns.boxplot(
    data=train_filt,
    x='sii', y='CGAS-CGAS_Score',
    palette='Set3', ax=axes[0]
)
axes[0].set_xlabel('SII Score')
axes[0].set_ylabel('CGAS Score')
axes[0].set_title('Distribution of CGAS Scores by SII')

# complete_resp_total vs CGAS_Score_Bin
sns.boxplot(
    data=train_filt,
```

```
    x='CGAS_Score_Bin', y='complete_resp_total',
    ax=axes[1], palette='Set3'
)

# Get the tick positions and match the labels
range_labels = [label.split(":")[0] for label in
train_filt['CGAS_Score_Bin'].cat.categories]
axes[1].set_xticklabels(range_labels)

axes[1].set_xlabel('CGAS Score category')
axes[1].set_ylabel('PCIAT_Total for Complete PCIAT Responses')
axes[1].set_title('Distribution of PCIAT_Total by CGAS Score
categories')

plt.tight_layout()
plt.show()
```




```
score_min_max = train.groupby('sii')['CGAS-CGAS_Score'].agg(['min',
'max'])
score_min_max = score_min_max.rename(
    columns={'min': 'Minimum CGAS Score', 'max': 'Maximum CGAS Score'}
)
score_min_max
```

	Minimum CGAS Score	Maximum CGAS Score
sii		
Missing	40.0	85.0
0 (None)	25.0	95.0
1 (Mild)	30.0	95.0
2 (Moderate)	35.0	85.0
3 (Severe)	35.0	80.0

Let's check the SII and Internet usage data for the participants with the worst global functioning:

```
train_filt[train_filt['CGAS-CGAS_Score'] < 35][
    ['Basic_Demos-Age', 'Basic_Demos-Sex', 'sii',
     'CGAS-CGAS_Score',
```

```
     'PreInt_EduHx-computerinternet_hoursday']
]

      Basic_Demos-Age Basic_Demos-Sex       sii  CGAS-CGAS_Score  \
2417                9          Female  0 (None)             31.0
2525               13          Female  1 (Mild)             30.0
2555               15            Male  0 (None)             33.0
3332               12            Male  0 (None)             25.0
3858               15            Male  0 (None)             31.0

      PreInt_EduHx-computerinternet_hoursday
2417                                     0.0
2525                                     0.0
2555                                     2.0
3332                                     2.0
3858                                     3.0
```

And the same for the participants with the best global functioning:

```
train[train['CGAS-CGAS_Score'] > 90][
    ['Basic_Demos-Age', 'Basic_Demos-Sex', 'sii',
     'CGAS-CGAS_Score',
     'PreInt_EduHx-computerinternet_hoursday']
]

      Basic_Demos-Age Basic_Demos-Sex       sii  CGAS-CGAS_Score  \
310                13          Female  0 (None)             91.0
591                10          Female  0 (None)             93.0
667                13            Male  0 (None)             95.0
910                10          Female  0 (None)             91.0
1007               14            Male  1 (Mild)             95.0
1157               14          Female  1 (Mild)             91.0
1640               11          Female  0 (None)             92.0
2342                6          Female  0 (None)             91.0
2668               14          Female  0 (None)             92.0
2675               11            Male  0 (None)             91.0
2926                7            Male  0 (None)             95.0
3165               17          Female  0 (None)             91.0
3467               15          Female  0 (None)             91.0
3484               14            Male  1 (Mild)             91.0
3713                7          Female  0 (None)             95.0
3749               10          Female  1 (Mild)             91.0

      PreInt_EduHx-computerinternet_hoursday
310                                      2.0
591                                      NaN
667                                      0.0
910                                      0.0
1007                                     0.0
1157                                     2.0
```

```
1640                                    0.0
2342                                    0.0
2668                                    0.0
2675                                    0.0
2926                                    0.0
3165                                    1.0
3467                                    0.0
3484                                    3.0
3713                                    0.0
3749                                    2.0
```

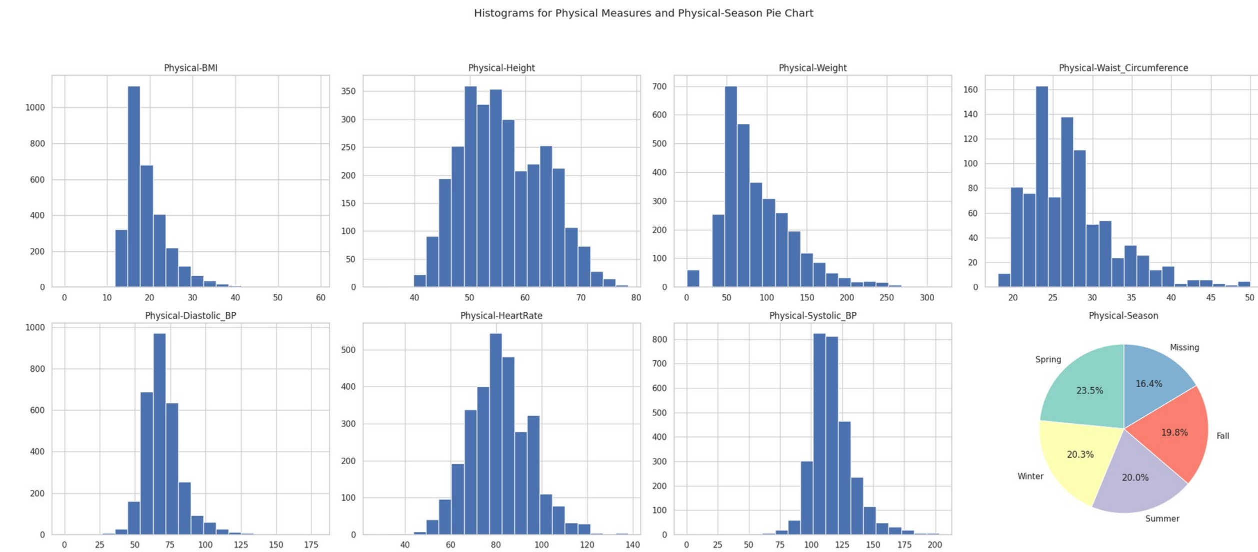
- Physical Measures

```
groups.get('Physical Measures', [])
```

```
['Physical-Season',
 'Physical-BMI',
 'Physical-Height',
 'Physical-Weight',
 'Physical-Waist_Circumference',
 'Physical-Diastolic_BP',
 'Physical-HeartRate',
 'Physical-Systolic_BP']
```

```
features_physical = groups.get('Physical Measures', [])
cols = [col for col in features_physical if col in continuous_cols]

plt.figure(figsize=(24, 10))
n_cols = 4
n_rows = len(cols) // n_cols + 1

for i, col in enumerate(cols):
    plt.subplot(n_rows, n_cols, i + 1)
    train[col].hist(bins=20)
    plt.title(col)

plt.subplot(n_rows, n_cols, len(cols) + 1)
season_counts = train['Physical-Season'].value_counts(dropna=False)
plt.pie(
    season_counts,
    labels=season_counts.index,
    autopct='%1.1f%%',
    startangle=90,
    colors=sns.color_palette("Set3")
)
plt.title('Physical-Season')

plt.suptitle('Histograms for Physical Measures and Physical-Season Pie
```

```
Chart', y=1.05)
plt.tight_layout()
plt.show()
```




```
calculate_stats(train, cols)
```

```
                              count        mean        std   min
25%  \
Physical-BMI                 3022.0   19.331929   5.113934   0.0
15.86935
Physical-Height              3027.0   55.946713   7.473764  33.0
50.00000
Physical-Weight              3076.0   89.038615  44.569040   0.0
57.20000
Physical-Waist_Circumference  898.0   27.278508   5.567287  18.0
23.00000
Physical-Diastolic_BP        2954.0   69.648951  13.611226   0.0
61.00000
Physical-HeartRate           2967.0   81.597236  13.665196  27.0
72.00000
Physical-Systolic_BP         2954.0  116.983074  17.061225   0.0
107.00000

                                    50%         75%         max
missing
Physical-BMI                  17.937682   21.571244   59.132048
938
Physical-Height               55.000000   62.000000   78.500000
933
Physical-Weight               77.000000  113.800000  315.000000
884
Physical-Waist_Circumference  26.000000   30.000000   50.000000
```

```
3062
Physical-Diastolic_BP          68.000000   76.000000  179.000000
1006
Physical-HeartRate             81.000000   90.500000  138.000000
993
Physical-Systolic_BP          114.000000  125.000000  203.000000
1006
```

Weight and Height

```
wh_cols = [
    'Physical-BMI', 'Physical-Height',
    'Physical-Weight', 'Physical-Waist_Circumference'
]
```

The minimum values of 0 for measures like BMI, weight, and blood pressure are biologically unrealistic, and likely indicate missing or erroneous data. Let's check number of zeros in these columns:

```
(train[wh_cols] == 0).sum()

Physical-BMI                     7
Physical-Height                  0
Physical-Weight                 61
Physical-Waist_Circumference     0
dtype: int64
```

Replace the 0 values by NaN and check the stats again:

```
train[wh_cols] = train[wh_cols].replace(0, np.nan)
calculate_stats(train, wh_cols)

                               count       mean        std        min
\
Physical-BMI                  3015.0  19.376812   5.034191   8.522436

Physical-Height               3027.0  55.946713   7.473764  33.000000

Physical-Weight               3015.0  90.840060  43.161374  31.800000

Physical-Waist_Circumference   898.0  27.278508   5.567287  18.000000


                                    25%        50%         75%
max  \
Physical-BMI                  15.890526  17.950925   21.588631
59.132048
Physical-Height               50.000000  55.000000   62.000000
78.500000
```

```
Physical-Weight                  58.200000  77.800000  114.300000
315.000000
Physical-Waist_Circumference  23.000000  26.000000   30.000000
50.000000

                              missing
Physical-BMI                      945
Physical-Height                   933
Physical-Weight                   945
Physical-Waist_Circumference     3062
```

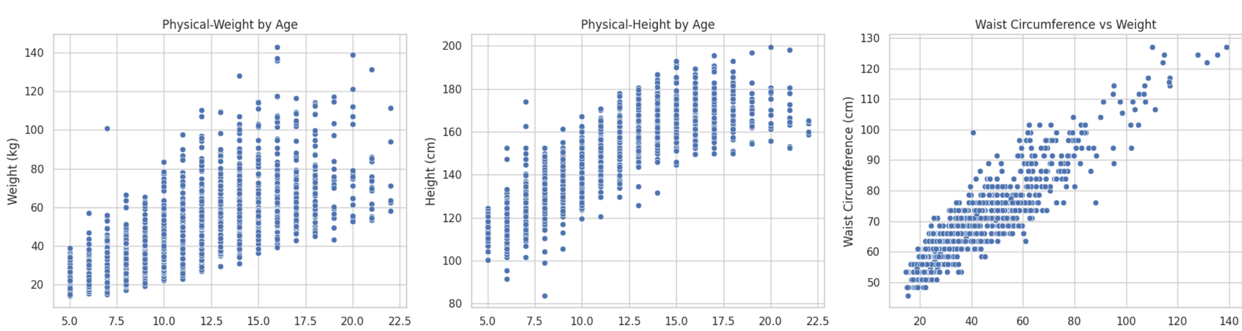
Convert weight to kilograms, and height to centimeters and recalculate BMI:

```
lbs_to_kg = 0.453592
inches_to_cm = 2.54

train['Physical-Weight'] = train['Physical-Weight'] * lbs_to_kg
train['Physical-Height'] = train['Physical-Height'] * inches_to_cm
train['Physical-Waist_Circumference'] = train['Physical-
Waist_Circumference'] * inches_to_cm

# Recalculate BMI: BMI = weight (kg) / (height (m)^2)
train['Physical-BMI'] = np.where(
    train['Physical-Weight'].notna() & train['Physical-
Height'].notna(),
    train['Physical-Weight'] / ((train['Physical-Height'] / 100) **
2),
    np.nan  # If either is NaN, set BMI to NaN
)

calculate_stats(train, wh_cols)

                               count        mean        std        min
\
Physical-BMI                  3015.0   19.378674   5.034658   8.523273

Physical-Height               3027.0  142.104651  18.983360  83.820000

Physical-Weight               3015.0   41.204324  19.577654  14.424226

Physical-Waist_Circumference   898.0   69.287410  14.140909  45.720000


                                     25%         50%         75%
max  \
Physical-BMI                   15.892086   17.952687   21.590750
59.137852
Physical-Height               127.000000  139.700000  157.480000
199.390000
Physical-Weight                26.399054   35.289458   51.845566
```

```
142.881480
Physical-Waist_Circumference   58.420000   66.040000   76.200000
127.000000

                              missing
Physical-BMI                      945
Physical-Height                   933
Physical-Weight                   945
Physical-Waist_Circumference     3062
```

A lot of values seem to be out of normal ranges... especially max values of weight (142kg) and waist circumference (127cm).

```python
plt.figure(figsize=(18, 5))

# Physical-Weight by Age
plt.subplot(1, 3, 1)
sns.scatterplot(x='Basic_Demos-Age', y='Physical-Weight', data=train)
plt.title('Physical-Weight by Age')
plt.xlabel('Age')
plt.ylabel('Weight (kg)')

# Physical-Height by Age
plt.subplot(1, 3, 2)
sns.scatterplot(x='Basic_Demos-Age', y='Physical-Height', data=train)
plt.title('Physical-Height by Age')
plt.xlabel('Age')
plt.ylabel('Height (cm)')

# Physical-Waist_Circumference vs Physical-Weight
plt.subplot(1, 3, 3)
sns.scatterplot(x='Physical-Weight', y='Physical-Waist_Circumference',
data=train)
plt.title('Waist Circumference vs Weight')
plt.xlabel('Weight (kg)')
plt.ylabel('Waist Circumference (cm)')

plt.tight_layout()
plt.show()
```



Blood Pressure & Heart Rate

There is 1000% incorrect data in the BP/HR columns as the minimum values are lethal to humans. We can clean up these kinds of mistakes.

```
bp_hr_cols = [
    'Physical-Diastolic_BP', 'Physical-Systolic_BP',
    'Physical-HeartRate'
]

(train[bp_hr_cols] < 50).sum()
```

```
Physical-Diastolic_BP    88
Physical-Systolic_BP      2
Physical-HeartRate       12
dtype: int64
```

We also know that systolic BP cannot be lower than diastolic BP:

```
train[train['Physical-Systolic_BP'] <= train['Physical-Diastolic_BP']]
[bp_hr_cols]
```

	Physical-Diastolic_BP	Physical-Systolic_BP	Physical-HeartRate
1140	179.0	139.0	103.0
1879	117.0	114.0	114.0
2386	76.0	76.0	116.0
3199	0.0	0.0	NaN
3344	98.0	73.0	96.0

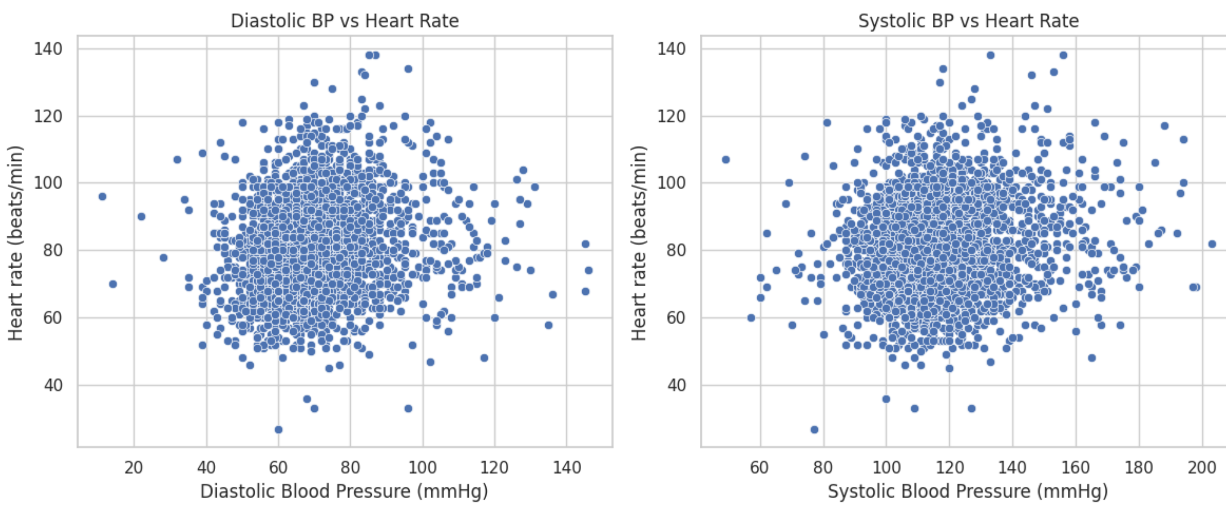
These are certainly incorrect measurements. But again, we can't be sure which information is correct, so we can either flag these rows for further manual inspection one by one, or replace all suspicious values with NaN. For this analysis I only remove 0 values and both BP if systolic is lower or equal to diastolic.

```
train[cols] = train[cols].replace(0, np.nan)
train.loc[train['Physical-Systolic_BP'] <= train['Physical-
Diastolic_BP'], bp_hr_cols] = np.nan
```

Blood Pressure vs Heart Rate

```
plt.figure(figsize=(12, 5))

# Diastolic BP vs Heart Rate
plt.subplot(1, 2, 1)
sns.scatterplot(x='Physical-Diastolic_BP', y='Physical-HeartRate',
data=train)
plt.title('Diastolic BP vs Heart Rate')
plt.xlabel('Diastolic Blood Pressure (mmHg)')
plt.ylabel('Heart rate (beats/min)')
```

```
# Systolic BP vs Heart Rate
plt.subplot(1, 2, 2)
sns.scatterplot(x='Physical-Systolic_BP', y='Physical-HeartRate',
data=train)
plt.title('Systolic BP vs Heart Rate')
plt.xlabel('Systolic Blood Pressure (mmHg)')
plt.ylabel('Heart rate (beats/min)')

plt.tight_layout()
plt.show()
```



Blood pressure vs Body Mass Index (BMI)

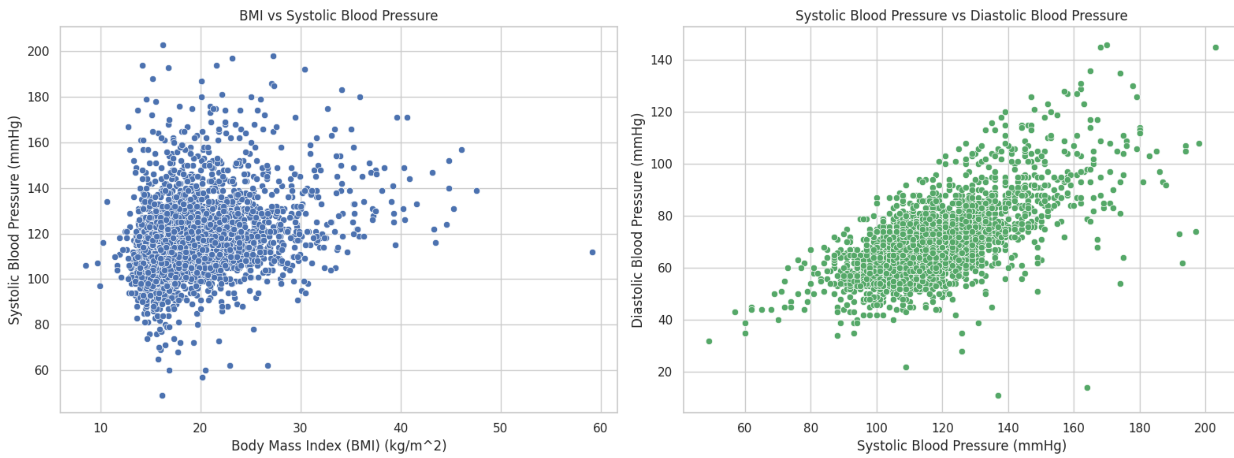
Typically, systolic (SBP) and diastolic (DBP) blood pressure are positively correlated, as they both reflect the functioning of the cardiovascular system. However, there can be deviations:

- Isolated Systolic Hypertension: High SBP with normal DBP
- Isolated Diastolic Hypertension: Normal SBP with high DBP
- General Hypertension: Both SBP and DBP are elevated

BMI is often used as an indicator of overall body fat and can correlate with blood pressure (e.g. higher BMI values indicating overweight or obesity are commonly associated with elevated blood pressure). Let's see if this is true for the study participants.

```
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# BMI vs Systolic Blood Pressure
sns.scatterplot(x='Physical-BMI', y='Physical-Systolic_BP',
data=train, ax=axes[0], color='b')
axes[0].set_title('BMI vs Systolic Blood Pressure')
axes[0].set_xlabel('Body Mass Index (BMI) (kg/m^2)')
axes[0].set_ylabel('Systolic Blood Pressure (mmHg)')
```

```python
# Systolic Blood Pressure vs Diastolic Blood Pressure
sns.scatterplot(
    x='Physical-Systolic_BP', y='Physical-Diastolic_BP',
    data=train, ax=axes[1], color='g'
)
axes[1].set_title('Systolic Blood Pressure vs Diastolic Blood
Pressure')
axes[1].set_xlabel('Systolic Blood Pressure (mmHg)')
axes[1].set_ylabel('Diastolic Blood Pressure (mmHg)')

plt.tight_layout()
plt.show()
```



Compare to normal rages

Now we'll define approximate normal ranges for each column and count the number of rows that fall outside these ranges. As normal values can vary widely between the ages of 5 and 22, **I use values that are general estimates; for more precise results you can refer to BMI-for-age growth charts on the CDC or WHO websites, for example.**

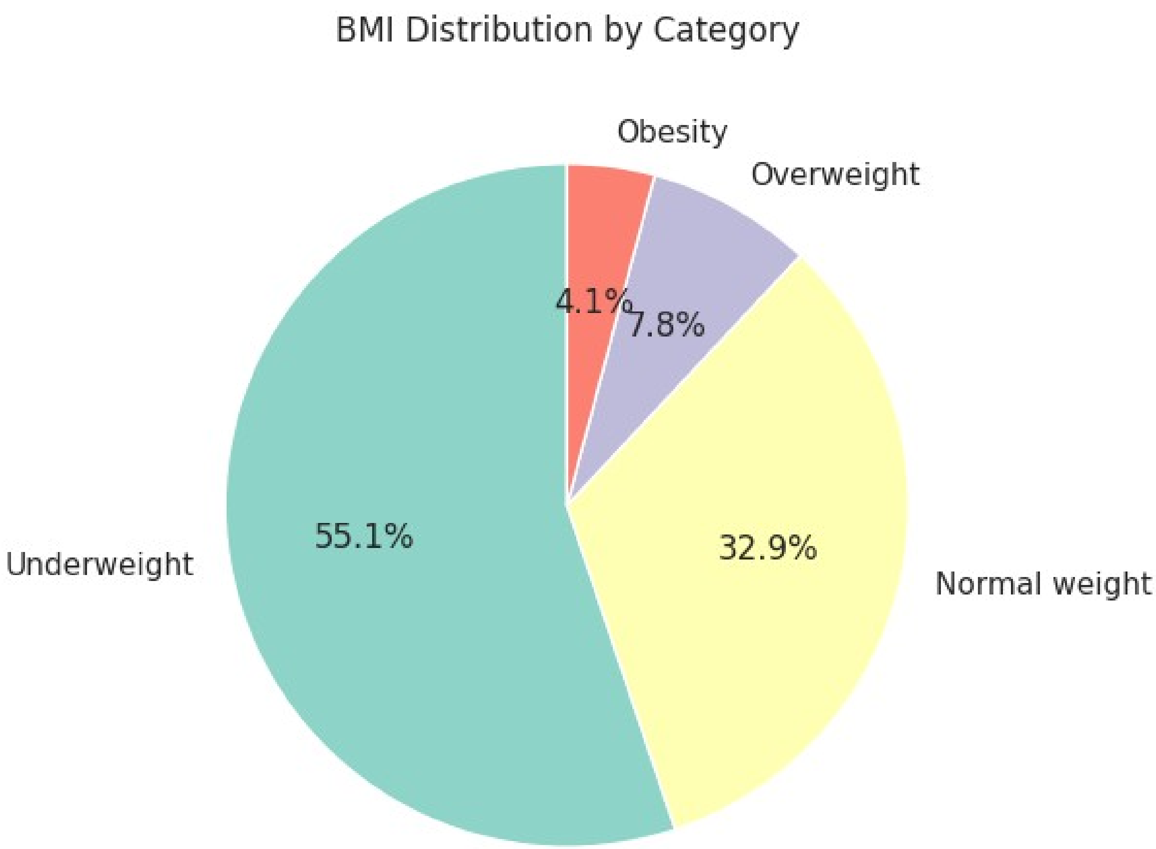
```python
normal_ranges = {
    'Physical-BMI': (18.5, 24.9),
    'Physical-Height': (100, 193),
    'Physical-Weight': (20, 120),
    'Physical-Waist_Circumference': (50, 90),
    'Physical-Diastolic_BP': (60, 80),
    'Physical-HeartRate': (60, 100),
    'Physical-Systolic_BP': (90, 120)
}

def count_out_of_range(data, column, low, high):
    return ((data[column] < low) | (data[column] > high)).sum()

out_of_range_counts = {
    col: count_out_of_range(train, col, *normal_ranges[col])
```

```
    for col in normal_ranges
}
print("Number of rows with values outside normal ranges:")

for col, count in out_of_range_counts.items():
    total_valid = train[col].notna().sum()
    percentage = (count / total_valid) * 100
    print(f"{col}: {count} ({percentage:.2f}%)")
```

```
Number of rows with values outside normal ranges:
Physical-BMI: 2027 (67.23%)
Physical-Height: 10 (0.33%)
Physical-Weight: 165 (5.47%)
Physical-Waist_Circumference: 93 (10.36%)
Physical-Diastolic_BP: 1019 (34.55%)
Physical-HeartRate: 347 (11.71%)
Physical-Systolic_BP: 1075 (36.45%)
```

Group BMI by obesity level according to WHO BMI-for-age (5-19 years)

```
bmi_categories = [
    ('Underweight', train['Physical-BMI'] < 18.5),
    ('Normal weight', (train['Physical-BMI'] >= 18.5) & 
(train['Physical-BMI'] <= 24.9)),
    ('Overweight', (train['Physical-BMI'] >= 25) & (train['Physical-
BMI'] <= 29.9)),
    ('Obesity', train['Physical-BMI'] >= 30)
]
bmi_category_counts = {label: condition.sum() for label, condition in 
bmi_categories}

plt.figure(figsize=(5, 6))
plt.pie(bmi_category_counts.values(), 
        labels=bmi_category_counts.keys(), 
        autopct='%1.1f%%', startangle=90, 
        colors=plt.cm.Set3.colors)
plt.title('BMI Distribution by Category')
plt.axis('equal')
plt.show()
```



Check extreme deviations cases

```
train[train['Physical-BMI'] < 12][cols + ['Basic_Demos-
Age']].sort_values(by = 'Physical-BMI')
```

```
      Physical-BMI  Physical-Height  Physical-Weight  \
2848      8.523273          149.860        19.141582
1952      9.694718          149.860        21.772416
3463      9.960144          152.400        23.133192
3324     10.282698          147.320        22.316726
1707     10.676487          162.560        28.213422
3143     11.468414          131.318        19.776611
1700     11.676989          167.005        32.567906
3636     11.713943          139.700        22.861037
1307     11.750716          112.522        14.877818
156      11.916424          149.860        26.761928
2023     11.926324          161.290        31.025693

      Physical-Waist_Circumference  Physical-Diastolic_BP  Physical-
HeartRate  \
2848                           NaN                   68.0
```

```
77.0
1952                                NaN                  64.0
86.0
3463                                NaN                  48.0
73.0
3324                                NaN                  72.0
72.0
1707                                NaN                  99.0
90.0
3143                                NaN                  59.0
77.0
1700                                NaN                  50.0
90.0
3636                                NaN                  58.0
99.0
1307                              48.26                   NaN
77.0
156                               71.12                  76.0
83.0
2023                                NaN                  59.0
65.0

      Physical-Systolic_BP  Basic_Demos-Age
2848                 106.0                8
1952                 107.0                7
3463                  97.0                6
3324                 116.0                6
1707                 134.0                7
3143                 110.0                8
1700                 106.0               10
3636                 104.0                7
1307                   NaN                7
156                  118.0               11
2023                 111.0                9
```

```
train[train['Physical-Systolic_BP'] > 160][cols + ['Basic_Demos-
Age']].sort_values(by = 'Physical-Systolic_BP')
```

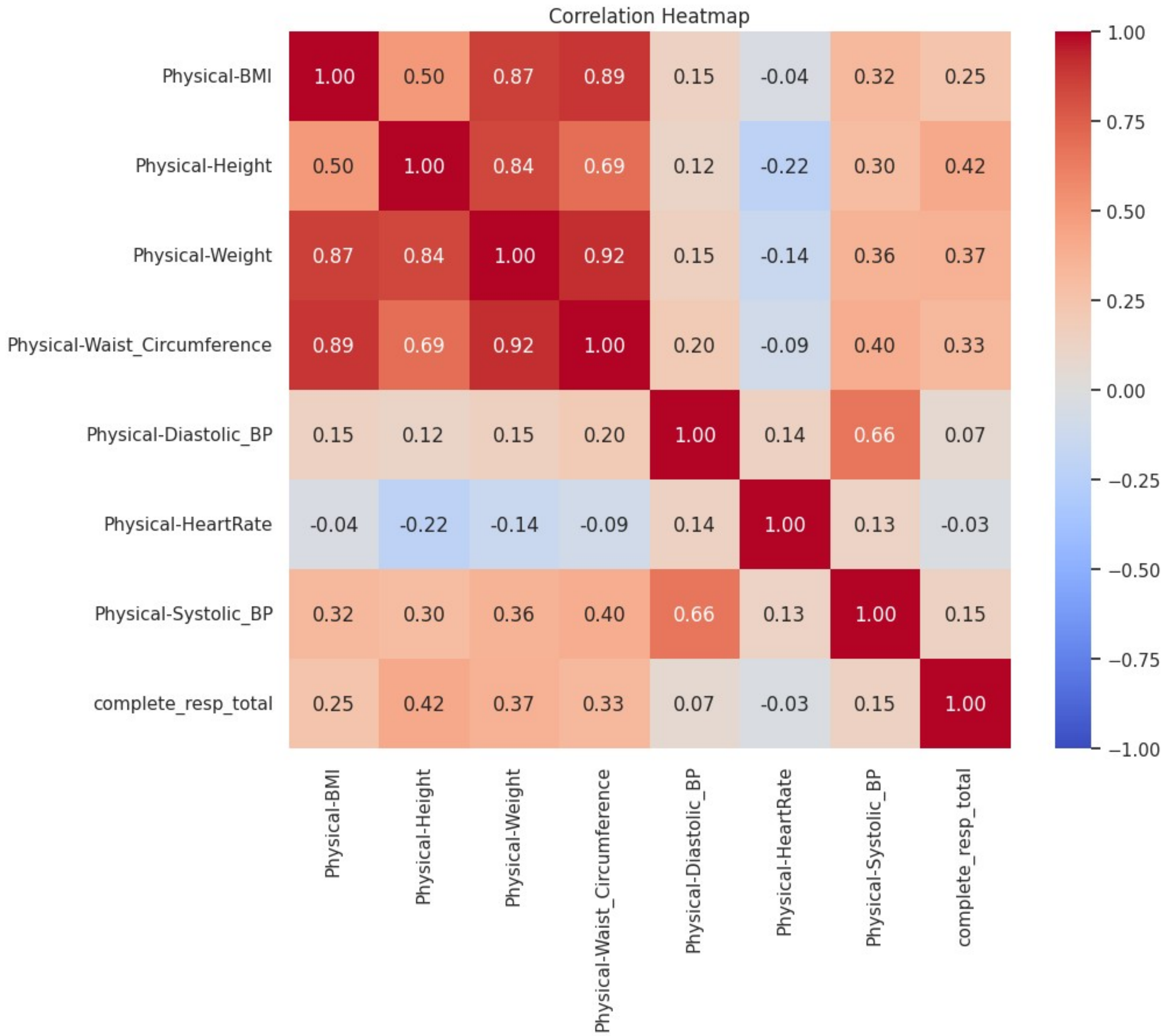
```
      Physical-BMI  Physical-Height  Physical-Weight  \
1794     14.036968          121.920        20.865232
284      21.719865          152.527        50.530149
3032     14.272220          129.540        23.949658
2401     17.245599          129.540        28.939170
882      16.398111          124.460        25.401152
...            ...              ...              ...
1019     14.172653          124.460        21.953853
2777     21.625191          134.620        39.190349
2549     23.154916          169.926        66.859461
436      27.260353          175.260        83.733083
3471     16.250635          137.160        30.572101
```

```
      Physical-Waist_Circumference  Physical-Diastolic_BP  Physical-
HeartRate  \
1794                           NaN                  111.0
69.0
284                            NaN                   96.0
99.0
3032                           NaN                  104.0
89.0
2401                           NaN                   87.0
103.0
882                            NaN                  127.0
95.0
...                            ...                    ...
...
1019                         60.96                  107.0
113.0
2777                           NaN                  105.0
100.0
2549                           NaN                   74.0
69.0
436                            NaN                  108.0
69.0
3471                           NaN                  145.0
82.0

      Physical-Systolic_BP  Basic_Demos-Age
1794                 161.0                8
284                  161.0               12
3032                 161.0                9
2401                 161.0                8
882                  161.0                6
...                    ...              ...
1019                 194.0                8
2777                 194.0                7
2549                 197.0               17
436                  198.0               19
3471                 203.0                9

[73 rows x 8 columns]
```

Relationships with the target variable (PCIAT_Total for complete PCIAT responses)

```
data_subset = train[cols + ['complete_resp_total']]

corr_matrix = data_subset.corr()

plt.figure(figsize=(10, 8))
```

```
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f',
vmin=-1, vmax=1)
plt.title('Correlation Heatmap')
plt.show()
```



- Bio-electric Impedance Analysis

```
data_dict[data_dict['Instrument'] == 'Bio-electric Impedance
Analysis']
```

```
                         Instrument                         Field  \
33  Bio-electric Impedance Analysis                    BIA-Season
34  Bio-electric Impedance Analysis  BIA-BIA_Activity_Level_num
35  Bio-electric Impedance Analysis                   BIA-BIA_BMC
```

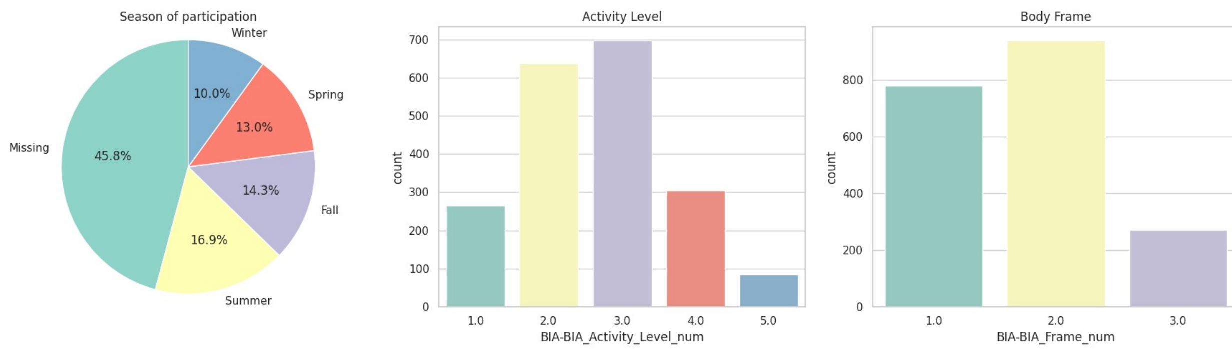
```
36  Bio-electric Impedance Analysis                 BIA-BIA_BMI
37  Bio-electric Impedance Analysis                 BIA-BIA_BMR
38  Bio-electric Impedance Analysis                 BIA-BIA_DEE
39  Bio-electric Impedance Analysis                 BIA-BIA_ECW
40  Bio-electric Impedance Analysis                 BIA-BIA_FFM
41  Bio-electric Impedance Analysis                BIA-BIA_FFMI
42  Bio-electric Impedance Analysis                 BIA-BIA_FMI
43  Bio-electric Impedance Analysis                 BIA-BIA_Fat
44  Bio-electric Impedance Analysis           BIA-BIA_Frame_num
45  Bio-electric Impedance Analysis                 BIA-BIA_ICW
46  Bio-electric Impedance Analysis                 BIA-BIA_LDM
47  Bio-electric Impedance Analysis                 BIA-BIA_LST
48  Bio-electric Impedance Analysis                 BIA-BIA_SMM
49  Bio-electric Impedance Analysis                 BIA-BIA_TBW

                 Description             Type
Values  \
33   Season of participation              str  Spring, Summer, Fall,
Winter
34            Activity Level  categorical int
1,2,3,4,5
35      Bone Mineral Content            float
NaN
36           Body Mass Index            float
NaN
37      Basal Metabolic Rate            float
NaN
38  Daily Energy Expenditure            float
NaN
39       Extracellular Water            float
NaN
40             Fat Free Mass            float
NaN
41       Fat Free Mass Index            float
NaN
42            Fat Mass Index            float
NaN
43       Body Fat Percentage            float
NaN
44               Body Frame  categorical int
1,2,3
45       Intracellular Water            float
NaN
46             Lean Dry Mass            float
NaN
47          Lean Soft Tissue            float
NaN
48      Skeletal Muscle Mass            float
NaN
```

```
49          Total Body Water             float
NaN

                                        Value Labels
33                                               NaN
34  1=Very Light, 2=Light, 3=Moderate, 4=Heavy, 5=...
35                                               NaN
36                                               NaN
37                                               NaN
38                                               NaN
39                                               NaN
40                                               NaN
41                                               NaN
42                                               NaN
43                                               NaN
44                           1=Small, 2=Medium, 3=Large
45                                               NaN
46                                               NaN
47                                               NaN
48                                               NaN
49                                               NaN
```

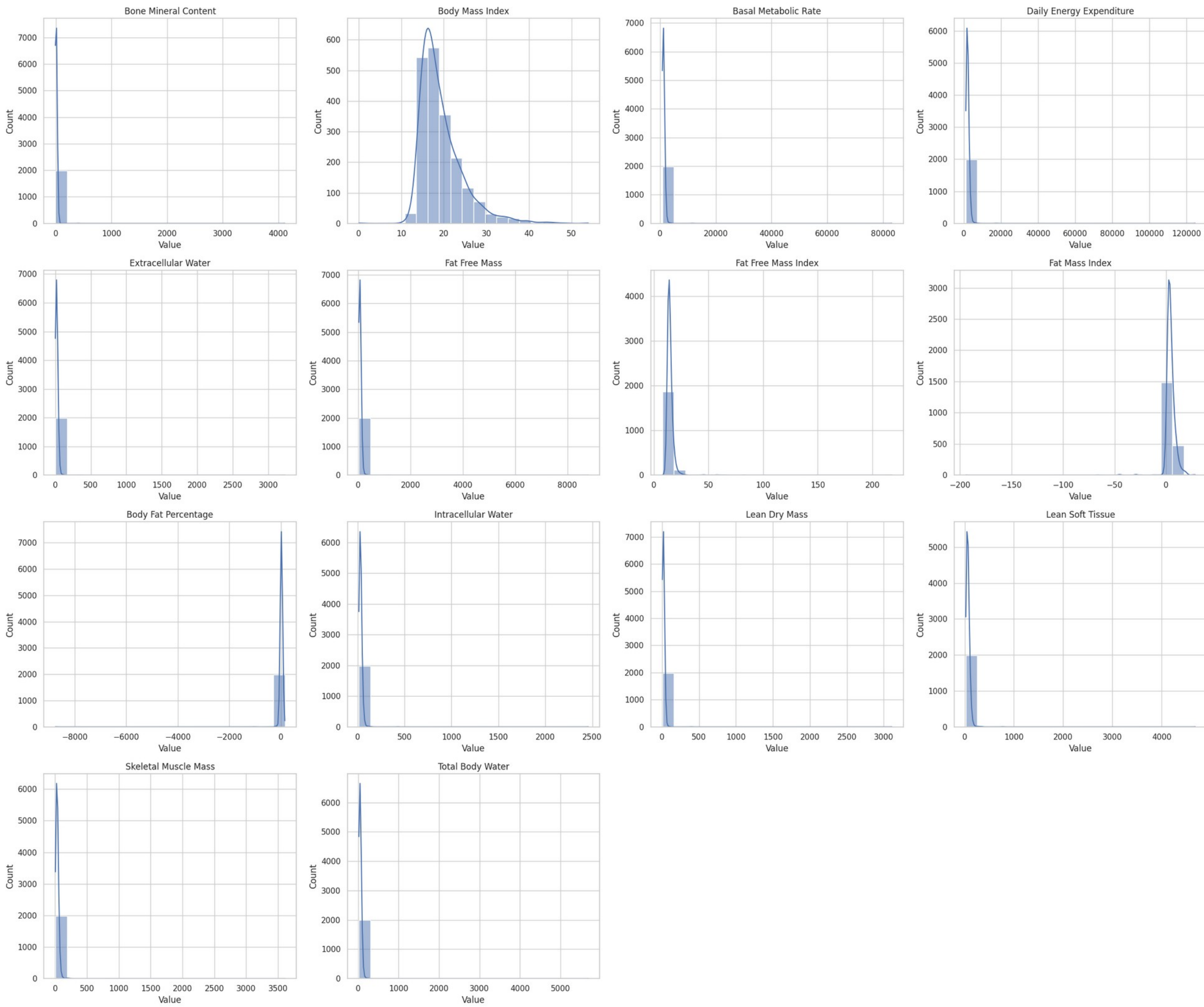
There is no information in the competition description about what equipment was used, is this raw data or did they use some BIA equation models to estimate the parameters. But it's likely that the BIA data has already been processed using a BIA equation model. It is very important to note that BIA is not a precise method, for example it tends to overestimate muscle mass, so equations have been developed to estimate muscle mass based on factors such as age, sex, height, weight and resistance and/or reactance estimated by BIA... a large number of prediction equation models have been generated through various validation studies (link). It is essential that all recordings are processed with the same equation, but we cannot be sure.

```
bia_data_dict = data_dict[data_dict['Instrument'] == 'Bio-electric
Impedance Analysis']
categorical_columns = bia_data_dict[bia_data_dict['Type'] ==
'categorical int']['Field'].tolist()
continuous_columns = bia_data_dict[bia_data_dict['Type'] == 'float']
['Field'].tolist()

fig, axes = plt.subplots(1, 3, figsize=(18, 5))

# Season
season_counts = train['BIA-Season'].value_counts(normalize=True)
axes[0].pie(
    season_counts,
    labels=season_counts.index,
    autopct='%1.1f%%',
    startangle=90,
    colors=sns.color_palette("Set3")
)
```

```
axes[0].set_title(
    f"{bia_data_dict[bia_data_dict['Field'] == 'BIA-Season']
['Description'].values[0]}"
)
axes[0].axis('equal')

# Other categorical columns
for idx, col in enumerate(categorical_columns):
    sns.countplot(x=col, data=train, palette="Set3", ax=axes[idx+1])
    axes[idx+1].set_title(data_dict[data_dict['Field'] == col]
['Description'].values[0])

plt.tight_layout()
plt.show()
```




```
plt.figure(figsize=(24, 20))

for idx, col in enumerate(continuous_columns):
    plt.subplot(4, 4, idx + 1)
    sns.histplot(train[col].dropna(), bins=20, kde=True)
    plt.title(data_dict[data_dict['Field'] == col]
['Description'].values[0])
    plt.xlabel('Value')

plt.tight_layout()
plt.show()
```

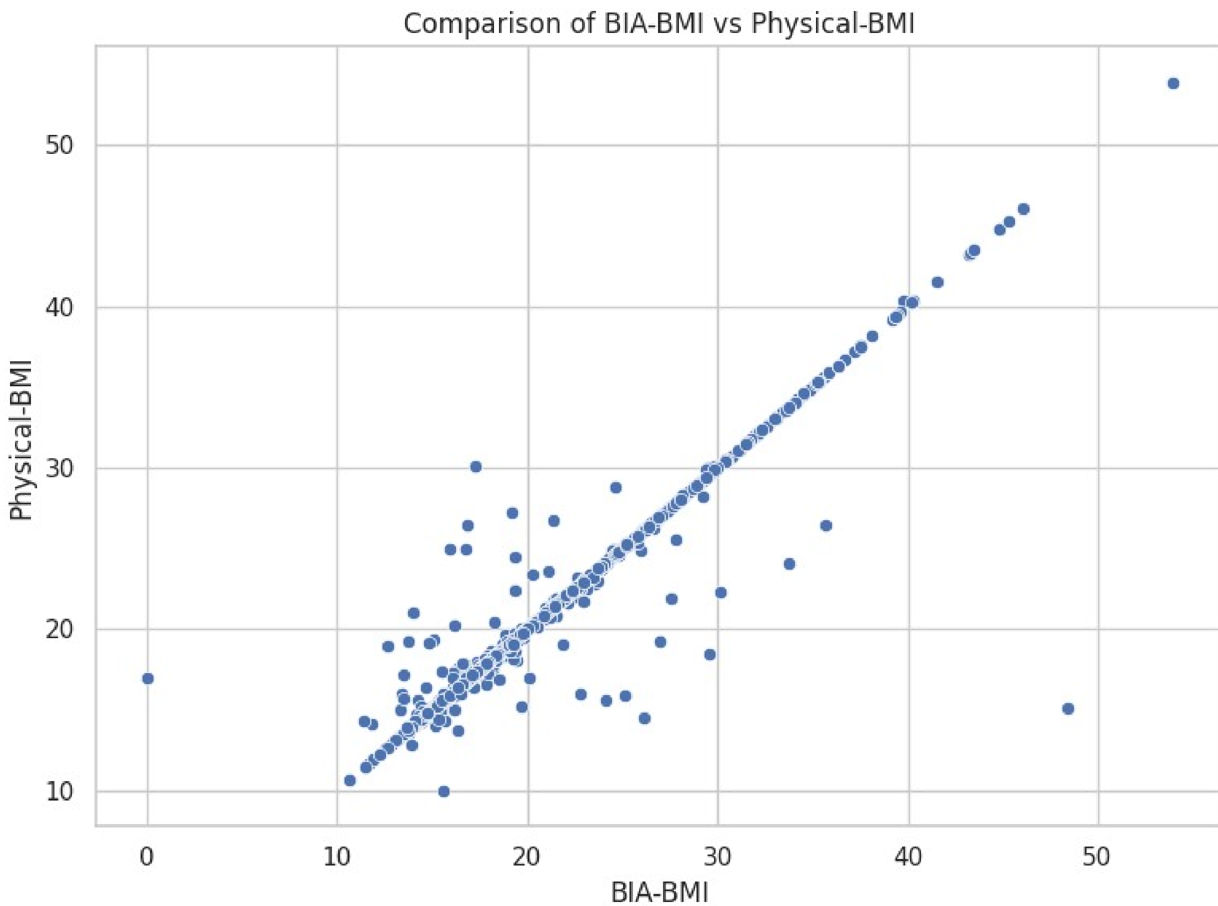



```
calculate_stats(train, continuous_columns)

               count         mean          std          min
25%  \
BIA-BIA_BMC   1991.0     6.719826    92.586325    -7.789610
2.966905
BIA-BIA_BMI   1991.0    19.367048     5.047848     0.048267
15.913600
BIA-BIA_BMR   1991.0  1237.018187  1872.383246   813.397000
1004.710000
BIA-BIA_DEE   1991.0  2064.693747  2836.246272  1073.450000
1605.785000
BIA-BIA_ECW   1991.0    20.825346    73.266287     1.789450
11.109550
BIA-BIA_FFM   1991.0    74.021708   199.433753    28.900400
49.278100
BIA-BIA_FFMI  1991.0    15.030554     5.792505     7.864850
13.408000
```

```
BIA-BIA_FMI   1991.0     4.336495     6.356402  -194.163000
2.306915
BIA-BIA_Fat   1991.0    16.855020   199.372119 -8745.080000
8.602395
BIA-BIA_ICW   1991.0    33.173380    56.272346    14.489000
24.463500
BIA-BIA_LDM   1991.0    20.022990    70.215610     4.635810
12.983150
BIA-BIA_LST   1991.0    67.301883   108.705918    23.620100
45.204100
BIA-BIA_SMM   1991.0    34.389466    84.050607     4.655730
21.141550
BIA-BIA_TBW   1991.0    53.998726   129.362539    20.589200
35.887000

                     50%          75%          max  missing
BIA-BIA_BMC      3.92272     5.460925    4115.3600     1969
BIA-BIA_BMI     17.96650    21.461100      53.9243     1969
BIA-BIA_BMR   1115.38000  1310.360000   83152.2000     1969
BIA-BIA_DEE   1863.98000  2218.145000  124728.0000     1969
BIA-BIA_ECW     15.92800    25.162200    3233.0000     1969
BIA-BIA_FFM     61.06620    81.833800    8799.0800     1969
BIA-BIA_FFMI    14.09250    15.430950     217.7710     1969
BIA-BIA_FMI      3.69863     5.987690      28.2515     1969
BIA-BIA_Fat     16.17460    30.273100     153.8200     1969
BIA-BIA_ICW     28.85580    35.475700    2457.9100     1969
BIA-BIA_LDM     16.43880    22.167600    3108.1700     1969
BIA-BIA_LST     56.99640    77.105650    4683.7100     1969
BIA-BIA_SMM     27.41510    38.179400    3607.6900     1969
BIA-BIA_TBW     44.98700    60.271050    5690.9100     1969
```

Compare the two measured BMI

```
bmi_data = train[['BIA-BIA_BMI', 'Physical-BMI']].dropna()

plt.figure(figsize=(8, 6))
sns.scatterplot(
    x='BIA-BIA_BMI', y='Physical-BMI',
    data=bmi_data,
    color='b'
)
plt.title('Comparison of BIA-BMI vs Physical-BMI')
plt.xlabel('BIA-BMI')
plt.ylabel('Physical-BMI')

plt.tight_layout()
plt.show()
```




```
bmi_measures = train[['BIA-Season', 'Physical-Season']].dropna()
bmi_measures.groupby(['BIA-Season', 'Physical-
Season']).size().reset_index(name='Count')
```

	BIA-Season	Physical-Season	Count
0	Fall	Fall	407
1	Fall	Missing	6
2	Fall	Spring	15
3	Fall	Summer	131
4	Fall	Winter	8
5	Missing	Fall	294
6	Missing	Missing	635
7	Missing	Spring	309
8	Missing	Summer	277
9	Missing	Winter	300
10	Spring	Fall	3
11	Spring	Missing	4
12	Spring	Spring	414
13	Spring	Summer	6
14	Spring	Winter	86
15	Summer	Fall	37
16	Summer	Missing	4

```
17      Summer          Spring    185
18      Summer          Summer    367
19      Summer          Winter     76
20      Winter            Fall     45
21      Winter         Missing      1
22      Winter          Spring      6
23      Winter          Summer     10
24      Winter          Winter    334
```

I am afraid that it will be meaningless to examine the relationships with the target variable, as there is too much unknown about these data (how they were collected and processed, what the reference values are, etc.).

- FitnessGram

FitnessGram Vitals and Treadmill

```
groups.get('FitnessGram Vitals and Treadmill', [])
```

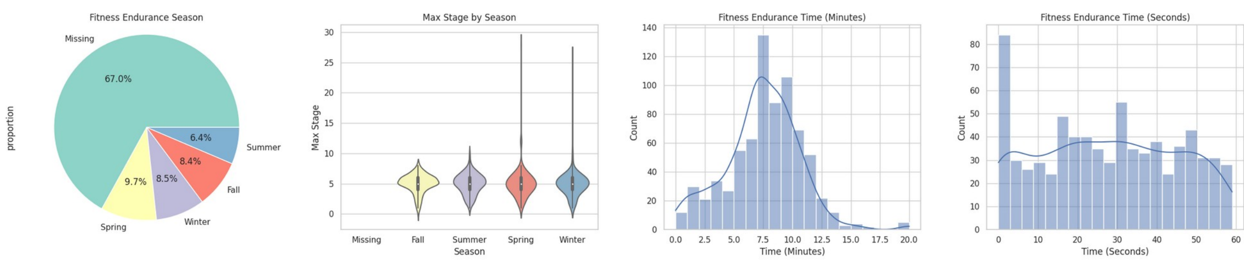
```
['Fitness_Endurance-Season',
 'Fitness_Endurance-Max_Stage',
 'Fitness_Endurance-Time_Mins',
 'Fitness_Endurance-Time_Sec']
```

```
data = train[train['Fitness_Endurance-Max_Stage'].notnull()]
age_range = data['Basic_Demos-Age']
print(
    f"Age range for participants with Fitness_Endurance-Max_Stage
data:"
    f" {age_range.min()} - {age_range.max()} years"
)
```

```
Age range for participants with Fitness_Endurance-Max_Stage data: 6 -
12 years
```

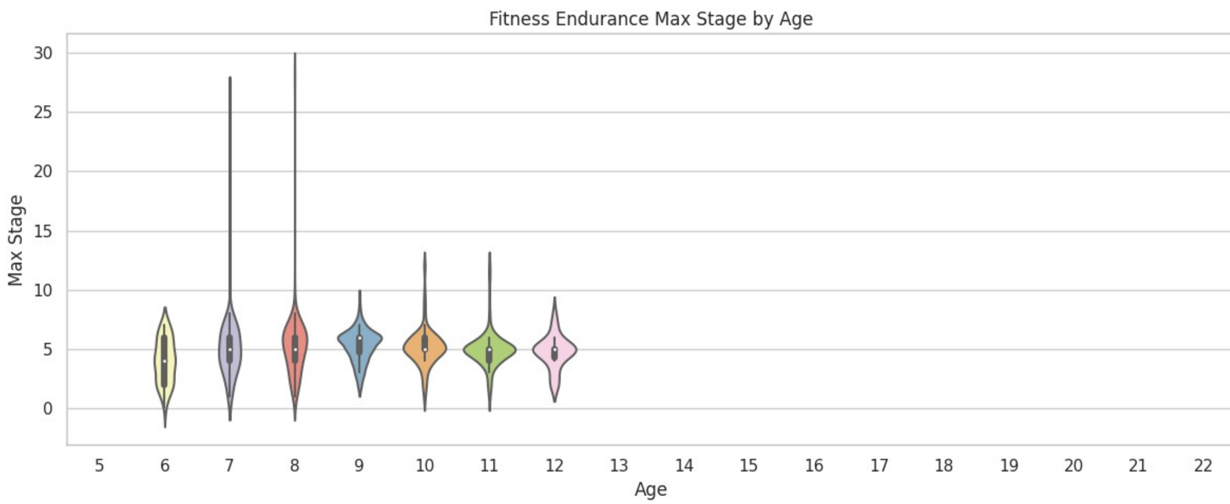
```
fig, axes = plt.subplots(1, 4, figsize=(24, 5))

# Fitness Endurance Season
train['Fitness_Endurance-
Season'].value_counts(normalize=True).plot.pie(
    autopct='%1.1f%%', colors=plt.cm.Set3.colors, ax=axes[0]
)
axes[0].set_title('Fitness Endurance Season')
axes[0].axis('equal')  # Equal aspect ratio ensures the pie is drawn
as a circle.

# Box plot for Max Stage by Season
sns.violinplot(
```

```
    x='Fitness_Endurance-Season',
    y='Fitness_Endurance-Max_Stage',
    data=train, palette="Set3",
    ax=axes[1]
)
axes[1].set_title('Max Stage by Season')
axes[1].set_xlabel('Season')
axes[1].set_ylabel('Max Stage')

# Fitness Endurance Time (Minutes)
sns.histplot(train['Fitness_Endurance-Time_Mins'], bins=20, kde=True,
ax=axes[2])
axes[2].set_title('Fitness Endurance Time (Minutes)')
axes[2].set_xlabel('Time (Minutes)')

# Fitness Endurance Time (Seconds)
sns.histplot(train['Fitness_Endurance-Time_Sec'], bins=20, kde=True,
ax=axes[3])
axes[3].set_title('Fitness Endurance Time (Seconds)')
axes[3].set_xlabel('Time (Seconds)')

plt.tight_layout()
plt.show()
```



Endurance by age:

```
plt.figure(figsize=(12, 5))

sns.violinplot(x='Basic_Demos-Age', y='Fitness_Endurance-Max_Stage',
data=train, palette="Set3")
plt.title('Fitness Endurance Max Stage by Age')
plt.xlabel('Age')
plt.ylabel('Max Stage')

plt.tight_layout()
plt.show()
```




```
cols = [
    'Fitness_Endurance-Max_Stage',
    'Fitness_Endurance-Time_Mins',
    'Fitness_Endurance-Time_Sec'
]
calculate_stats(train, cols)
```

```
                             count       mean        std  min    25%
50%  \
Fitness_Endurance-Max_Stage  743.0   4.989233   2.014072  0.0   4.00
5.0
Fitness_Endurance-Time_Mins  740.0   7.370270   3.189662  0.0   6.00
7.0
Fitness_Endurance-Time_Sec   740.0  27.581081  17.707751  0.0  12.75
28.0

                              75%   max  missing
Fitness_Endurance-Max_Stage   6.0  28.0     3217
Fitness_Endurance-Time_Mins   9.0  20.0     3220
Fitness_Endurance-Time_Sec   43.0  59.0     3220
```

- Fitness_Endurance-Max_Stage: likely represents the maximum stage reached during an endurance test. In fitness endurance tests like a treadmill test or a multi-stage fitness test (beep test), participants progress through increasing levels of difficulty (speed or incline), and this column records the highest level or stage completed by the participant before stopping.
- Fitness_Endurance-Time_Mins: could be the duration a participant was able to sustain the test before reaching exhaustion, measured in minutes
- Fitness_Endurance-Time_Sec: I guess combining both columns (minutes and seconds) would give the exact total time of the endurance test completed by the participants.

Check the combinations of missing values

Max_Stage present, time (mins or secs) missing:

```
train[
    (train['Fitness_Endurance-Max_Stage'].notna()) &
    (train['Fitness_Endurance-Time_Mins'].isna() |
     train['Fitness_Endurance-Time_Sec'].isna())
][cols]
```

```
      Fitness_Endurance-Max_Stage  Fitness_Endurance-Time_Mins  \
420                           4.0                          6.0
1470                         26.0                          NaN
2907                          1.0                          NaN
3666                          2.0                          NaN

      Fitness_Endurance-Time_Sec
420                          NaN
1470                         NaN
2907                        26.0
3666                         NaN
```

It's possible that during data entry minutes or seconds were left blank (entered as NaN) when they should have been recorded as 0 minutes/seconds. While the missing seconds are not as important, the missing minutes may actually be missing and treating them as 0 would give an incorrect test result. I think it's better to just remove these suspicious cases.

```
train.loc[
    (train['Fitness_Endurance-Max_Stage'].notna()) &
    (train['Fitness_Endurance-Time_Mins'].isna() |
     train['Fitness_Endurance-Time_Sec'].isna()), cols
] = np.nan
```

Get one time column (mins + sec)

```
train['Fitness_Endurance-Total_Time_Sec'] = train[
    'Fitness_Endurance-Time_Mins'
] * 60 + train['Fitness_Endurance-Time_Sec']
```

Recalculate stats:

```
calculate_stats(train, ['Fitness_Endurance-Max_Stage',
'Fitness_Endurance-Total_Time_Sec'])
```

```
                                  count        mean         std  min
25%  \
Fitness_Endurance-Max_Stage       739.0    4.971583    1.856069  0.0
4.0
Fitness_Endurance-Total_Time_Sec  739.0  469.910690  188.716073  5.0
362.0

                                    50%    75%     max  missing
```

```
Fitness_Endurance-Max_Stage          5.0    6.0    28.0     3221
Fitness_Endurance-Total_Time_Sec   476.0  590.5  1200.0     3221
```

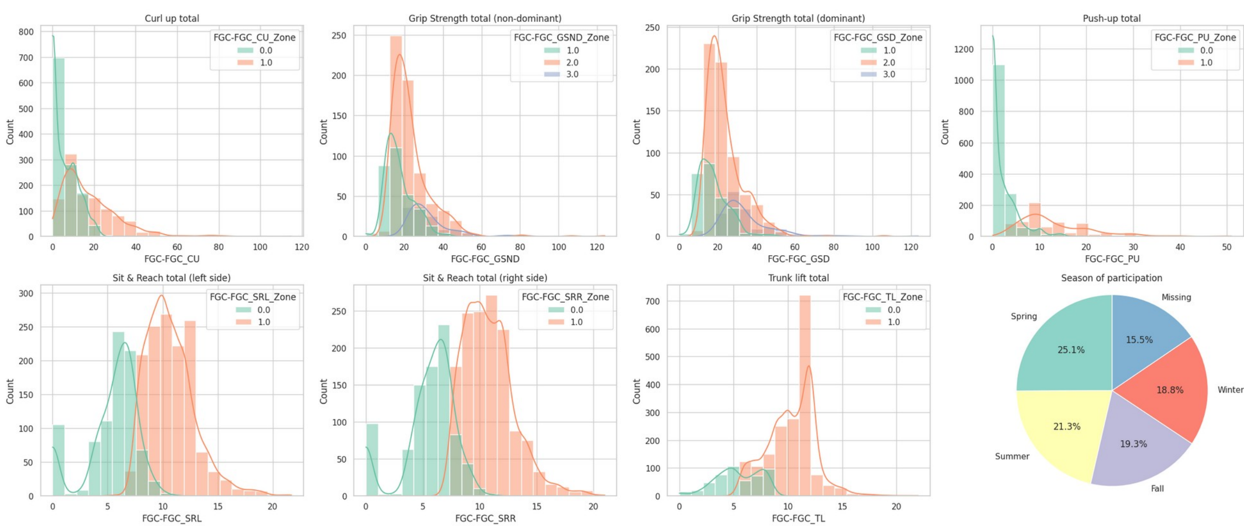
FitnessGram Child

```
data_dict[data_dict['Instrument'] == 'FitnessGram Child']
```

```
           Instrument              Field  \
18  FitnessGram Child         FGC-Season
19  FitnessGram Child         FGC-FGC_CU
20  FitnessGram Child    FGC-FGC_CU_Zone
21  FitnessGram Child       FGC-FGC_GSND
22  FitnessGram Child  FGC-FGC_GSND_Zone
23  FitnessGram Child        FGC-FGC_GSD
24  FitnessGram Child   FGC-FGC_GSD_Zone
25  FitnessGram Child         FGC-FGC_PU
26  FitnessGram Child    FGC-FGC_PU_Zone
27  FitnessGram Child        FGC-FGC_SRL
28  FitnessGram Child   FGC-FGC_SRL_Zone
29  FitnessGram Child        FGC-FGC_SRR
30  FitnessGram Child   FGC-FGC_SRR_Zone
31  FitnessGram Child         FGC-FGC_TL
32  FitnessGram Child    FGC-FGC_TL_Zone

                                  Description             Type  \
18                       Season of participation              str
19                                 Curl up total              int
20                            Curl up fitness zone  categorical int
21         Grip Strength total (non-dominant)            float
22  Grip Strength fitness zone (non-dominant)  categorical int
23             Grip Strength total (dominant)            float
24      Grip Strength fitness zone (dominant)  categorical int
25                                 Push-up total              int
26                            Push-up fitness zone  categorical int
27              Sit & Reach total (left side)            float
28       Sit & Reach fitness zone (left side)  categorical int
29             Sit & Reach total (right side)            float
30      Sit & Reach fitness zone (right side)  categorical int
31                              Trunk lift total              int
32                         Trunk lift fitness zone  categorical int

                          Values                                   Value
Labels
18  Spring, Summer, Fall, Winter
NaN
19                           NaN
NaN
20                           0,1  0=Needs Improvement, 1=Healthy
Fitness Zone
```

```
21                                  NaN
NaN
22                                1,2,3                       1=Weak, 2=Normal,
3=Strong
23                                  NaN
NaN
24                                1,2,3                       1=Weak, 2=Normal,
3=Strong
25                                  NaN
NaN
26                                  0,1  0=Needs Improvement, 1=Healthy
Fitness Zone
27                                  NaN
NaN
28                                  0,1  0=Needs Improvement, 1=Healthy
Fitness Zone
29                                  NaN
NaN
30                                  0,1  0=Needs Improvement, 1=Healthy
Fitness Zone
31                                  NaN
NaN
32                                  0,1  0=Needs Improvement, 1=Healthy
Fitness Zone

fgc_data_dict = data_dict[data_dict['Instrument'] == 'FitnessGram
Child']

fgc_columns = []

for index, row in fgc_data_dict.iterrows():
    if '_Zone' not in row['Field']:
        measure_field = row['Field']
        measure_desc = row['Description']

        zone_field = measure_field + '_Zone'
        zone_row = fgc_data_dict[fgc_data_dict['Field'] == zone_field]

        if not zone_row.empty:
            zone_desc = zone_row['Description'].values[0]
            fgc_columns.append((measure_field, zone_field,
measure_desc, zone_desc))

fig, axes = plt.subplots(2, 4, figsize=(24, 10))

for idx, (measure, zone, measure_desc, zone_desc) in
enumerate(fgc_columns):
    row = idx // 4
    col = idx % 4
```

```
    sns.histplot(
        data=train, x=measure,
        hue=zone, bins=20, palette='Set2',
        ax=axes[row, col], kde=True
    )
    axes[row, col].set_title(f'{measure_desc}')

season_counts = train['FGC-Season'].value_counts(normalize=True)
axes[1, 3].pie(
    season_counts, labels=season_counts.index,
    autopct='%1.1f%%', startangle=90,
    colors=sns.color_palette("Set3")
)
axes[1, 3].set_title('Season of participation')
axes[1, 3].axis('equal')

plt.tight_layout()
plt.show()
```




```
measurement_columns = [measure for measure, _, _, _ in fgc_columns]
calculate_stats(train, measurement_columns)

               count       mean        std  min   25%    50%     75%
max  \
FGC-FGC_CU    2322.0  11.259690  11.807781  0.0   3.0   9.00  15.750
115.0
FGC-FGC_GSND  1074.0  22.420438  10.833995  0.0  15.1  20.05  26.600
124.0
FGC-FGC_GSD   1074.0  23.518622  11.148951  0.0  16.2  21.20  28.175
123.8
FGC-FGC_PU    2310.0   5.579654   7.390161  0.0   0.0   3.00   9.000
51.0
FGC-FGC_SRL   2305.0   8.694924   3.429301  0.0   7.0   9.00  11.000
```

```
21.7
FGC-FGC_SRR    2307.0    8.805635    3.422167   0.0    7.0    9.00   11.000
21.0
FGC-FGC_TL     2324.0    9.252775    2.988863   0.0    7.0   10.00   12.000
22.0

              missing
FGC-FGC_CU       1638
FGC-FGC_GSND     2886
FGC-FGC_GSD      2886
FGC-FGC_PU       1650
FGC-FGC_SRL      1655
FGC-FGC_SRR      1653
FGC-FGC_TL       1636
```

Overlap between fitness zones

```python
def compute_min_max_by_sex(train, sex, fgc_columns):
    results = []

    for measure, zone, _, _ in fgc_columns:
        sorted_zones = sorted(train[zone].dropna().unique())

        for zone_value in sorted_zones:
            data = train[(train[zone] == zone_value) &
                         (train['Basic_Demos-Sex'] == sex)][measure]

            if not data.empty:
                min_val, max_val = data.min(), data.max()
                results.append({
                    'Zone': int(zone_value),
                    'Measure': measure,
                    'Min-Max': f'{min_val} - {max_val}'
                })

    df = pd.DataFrame(results).pivot_table(
        index='Zone', columns='Measure', values='Min-Max',
aggfunc='first'
    )

    return df
```

Output ranges for each measure and zone for males:

```python
compute_min_max_by_sex(train, 'Male', fgc_columns)
```

```
Measure   FGC-FGC_CU   FGC-FGC_GSD  FGC-FGC_GSND  FGC-FGC_PU FGC-
FGC_SRL  \
Zone
```

```
0          0.0 - 23.0           NaN           NaN  0.0 - 19.0  0.0 -
7.75
1          2.0 - 85.0    0.0 - 46.8    0.0 - 43.0  3.0 - 51.0  7.5 -
20.0
2                 NaN  12.7 - 106.0  12.6 - 106.4         NaN
NaN
3                 NaN  22.5 - 123.8   22.6 - 81.8         NaN
NaN

Measure FGC-FGC_SRR  FGC-FGC_TL
Zone
0          0.0 - 8.0   0.0 - 8.2
1         7.0 - 19.0  5.5 - 21.0
2                NaN         NaN
3                NaN         NaN
```

Same for females;

```
compute_min_max_by_sex(train, 'Female', fgc_columns)

Measure   FGC-FGC_CU  FGC-FGC_GSD FGC-FGC_GSND  FGC-FGC_PU FGC-FGC_SRL
\
Zone

0          0.0 - 17.0          NaN          NaN  0.0 - 6.0  0.0 - 11.0

1         2.0 - 115.0   5.1 - 49.8   0.0 - 36.2 3.0 - 50.0  5.5 - 21.7

2                 NaN   9.5 - 65.2  9.0 - 124.0        NaN         NaN

3                 NaN  16.3 - 88.8  15.5 - 74.0        NaN         NaN


Measure FGC-FGC_SRR  FGC-FGC_TL
Zone
0         0.0 - 11.0   0.0 - 8.5
1         8.5 - 21.0  5.5 - 22.0
2                NaN         NaN
3                NaN         NaN
```

The ranges for each measure and zone by age (only for males, just to check if the overlap still exists):

```
results_male = []

for measure, zone, _, _ in fgc_columns:
    sorted_zones = sorted(train[zone].dropna().unique())
    for zone_value in sorted_zones:
        age_sex_data_by_zone = train[train[zone] == zone_value][
```

```
            ['Basic_Demos-Age', 'Basic_Demos-Sex', measure]
        ]
        unique_ages = age_sex_data_by_zone['Basic_Demos-
Age'].dropna().unique()

        for age in sorted(unique_ages):
            age_sex_data = age_sex_data_by_zone[
                (age_sex_data_by_zone['Basic_Demos-Age'] == age) &
                (age_sex_data_by_zone['Basic_Demos-Sex'] == 'Male')
            ][measure]

            if not age_sex_data.empty:
                min_val, max_val = age_sex_data.min(),
age_sex_data.max()
                results_male.append({
                    'Age': age,
                    'Sex': 'Male',
                    'Zone': zone_value,
                    'Measure': measure,
                    'Min-Max': f'{min_val} - {max_val}'
                })

df_male = pd.DataFrame(results_male).pivot_table(
    index=['Age', 'Sex', 'Zone'], columns='Measure', values='Min-Max',
aggfunc='first'
)

df_male
```

```
Measure          FGC-FGC_CU   FGC-FGC_GSD  FGC-FGC_GSND   FGC-FGC_PU  \
Age Sex  Zone
5   Male 0.0      0.0 - 1.0           NaN           NaN    0.0 - 2.0
         1.0     2.0 - 13.0           NaN           NaN    3.0 - 8.0
6   Male 0.0      0.0 - 1.0           NaN           NaN    0.0 - 2.0
         1.0     2.0 - 40.0           NaN           NaN   3.0 - 20.0
7   Male 0.0      0.0 - 3.0           NaN           NaN    0.0 - 3.0
         1.0     2.0 - 30.0           NaN           NaN   3.0 - 24.0
8   Male 0.0      0.0 - 5.0           NaN           NaN    0.0 - 5.0
         1.0     4.0 - 30.0           NaN           NaN   4.0 - 40.0
9   Male 0.0     0.0 - 10.0           NaN           NaN    0.0 - 5.0
         1.0     6.0 - 43.0   11.1 - 11.1           NaN   5.0 - 30.0
         2.0            NaN   13.3 - 13.3   12.7 - 13.1          NaN
10  Male 0.0     0.0 - 11.0           NaN           NaN    0.0 - 6.0
         1.0     9.0 - 75.0    0.0 - 16.1    0.0 - 15.1   6.0 - 37.0
         2.0            NaN   12.7 - 44.0   12.6 - 34.0          NaN
         3.0            NaN   25.9 - 29.3   22.9 - 50.2          NaN
11  Male 0.0     0.0 - 14.0           NaN           NaN    0.0 - 7.0
         1.0    12.0 - 50.0    6.3 - 24.6    8.6 - 24.6   7.0 - 50.0
         2.0            NaN   12.8 - 35.4   12.7 - 49.0          NaN
         3.0            NaN   22.5 - 53.6   22.6 - 49.8          NaN
```

12	Male	0.0	0.0 - 17.0	NaN	NaN	0.0 - 9.0
		1.0	15.0 - 45.0	9.9 - 40.6	9.9 - 41.8	8.0 - 30.0
		2.0	NaN	13.1 - 49.0	12.6 - 48.2	NaN
		3.0	NaN	22.8 - 46.8	23.0 - 41.7	NaN
13	Male	0.0	0.0 - 20.0	NaN	NaN	0.0 - 19.0
		1.0	18.0 - 80.0	11.3 - 37.2	8.9 - 31.4	10.0 - 40.0
		2.0	NaN	19.1 - 47.8	17.7 - 45.6	NaN
		3.0	NaN	32.5 - 42.2	31.6 - 42.6	NaN
14	Male	0.0	0.0 - 23.0	NaN	NaN	0.0 - 13.0
		1.0	24.0 - 80.0	12.8 - 46.8	11.5 - 43.0	13.0 - 37.0
		2.0	NaN	19.7 - 42.9	20.2 - 56.8	NaN
		3.0	NaN	31.5 - 79.2	31.8 - 81.8	NaN
15	Male	0.0	0.0 - 23.0	NaN	NaN	0.0 - 14.0
		1.0	24.0 - 85.0	0.0 - 43.4	0.0 - 39.4	15.0 - 49.0
		2.0	NaN	22.6 - 76.8	17.5 - 80.4	NaN
		3.0	NaN	28.1 - 49.6	33.6 - 47.1	NaN
16	Male	0.0	0.0 - 23.0	NaN	NaN	0.0 - 15.0
		1.0	24.0 - 64.0	16.1 - 32.3	15.3 - 32.0	16.0 - 39.0
		2.0	NaN	29.2 - 47.9	21.6 - 46.6	NaN
		3.0	NaN	46.6 - 57.6	44.0 - 47.4	NaN
17	Male	0.0	0.0 - 22.0	NaN	NaN	0.0 - 15.0
		1.0	24.0 - 78.0	11.1 - 32.3	12.4 - 31.9	18.0 - 47.0
		2.0	NaN	17.8 - 106.0	30.4 - 106.4	NaN
		3.0	NaN	34.4 - 123.8	33.3 - 53.7	NaN
18	Male	0.0	0.0 - 23.0	NaN	NaN	5.0 - 14.0
		1.0	25.0 - 40.0	NaN	28.4 - 33.8	23.0 - 51.0
		2.0	NaN	24.4 - 52.0	20.2 - 42.1	NaN
		3.0	NaN	28.4 - 28.4	23.4 - 52.7	NaN
19	Male	0.0	8.0 - 20.0	NaN	NaN	8.0 - 8.0
		1.0	NaN	23.9 - 31.1	26.0 - 26.1	18.0 - 18.0
20	Male	0.0	NaN	NaN	NaN	17.0 - 17.0
		1.0	34.0 - 34.0	NaN	NaN	NaN
		3.0	NaN	56.8 - 56.8	52.5 - 52.5	NaN
21	Male	0.0	20.0 - 20.0	NaN	NaN	11.0 - 11.0
		1.0	30.0 - 30.0	NaN	23.3 - 23.3	20.0 - 20.0
		2.0	NaN	37.4 - 37.4	40.0 - 40.0	NaN

Measure			FGC-FGC_SRL	FGC-FGC_SRR	FGC-FGC_TL
Age	Sex	Zone			
5	Male	0.0	0.0 - 7.0	0.0 - 7.0	0.0 - 5.0
		1.0	8.0 - 16.5	8.0 - 17.0	5.5 - 13.0
6	Male	0.0	0.0 - 7.5	0.0 - 7.2	0.0 - 5.0
		1.0	7.5 - 18.0	7.5 - 17.0	5.5 - 14.0
7	Male	0.0	0.0 - 7.0	0.0 - 7.0	0.0 - 5.0
		1.0	7.5 - 19.0	7.5 - 18.0	6.0 - 15.0
8	Male	0.0	0.0 - 7.5	0.0 - 7.5	0.0 - 5.0
		1.0	7.5 - 20.0	7.5 - 19.0	5.5 - 18.0
9	Male	0.0	0.0 - 7.5	0.0 - 7.5	0.0 - 5.0
		1.0	7.5 - 15.0	7.5 - 15.0	5.5 - 15.0

		2.0	NaN	NaN	NaN
10	Male	0.0	0.0 - 7.5	0.0 - 7.5	2.0 - 8.2
		1.0	7.5 - 18.0	7.5 - 19.0	6.0 - 15.0
		2.0	NaN	NaN	NaN
		3.0	NaN	NaN	NaN
11	Male	0.0	0.0 - 7.5	0.0 - 7.0	1.0 - 8.0
		1.0	7.5 - 13.0	7.5 - 13.5	8.5 - 21.0
		2.0	NaN	NaN	NaN
		3.0	NaN	NaN	NaN
12	Male	0.0	0.0 - 7.5	0.0 - 7.0	1.5 - 8.0
		1.0	7.5 - 18.0	7.5 - 17.0	8.5 - 15.0
		2.0	NaN	NaN	NaN
		3.0	NaN	NaN	NaN
13	Male	0.0	0.0 - 7.0	0.0 - 7.3	3.0 - 8.0
		1.0	7.5 - 15.0	7.0 - 17.0	9.0 - 17.0
		2.0	NaN	NaN	NaN
		3.0	NaN	NaN	NaN
14	Male	0.0	0.0 - 7.25	0.0 - 7.0	4.0 - 8.0
		1.0	7.5 - 16.0	7.5 - 16.0	8.5 - 15.0
		2.0	NaN	NaN	NaN
		3.0	NaN	NaN	NaN
15	Male	0.0	0.0 - 7.0	0.0 - 7.5	1.0 - 8.0
		1.0	7.5 - 15.0	8.0 - 15.0	8.5 - 18.0
		2.0	NaN	NaN	NaN
		3.0	NaN	NaN	NaN
16	Male	0.0	0.0 - 7.75	0.0 - 7.5	4.0 - 8.0
		1.0	8.0 - 19.0	7.5 - 18.0	9.0 - 14.0
		2.0	NaN	NaN	NaN
		3.0	NaN	NaN	NaN
17	Male	0.0	0.0 - 6.5	0.0 - 8.0	0.0 - 8.0
		1.0	7.5 - 17.0	7.5 - 16.5	9.0 - 17.0
		2.0	NaN	NaN	NaN
		3.0	NaN	NaN	NaN
18	Male	0.0	3.0 - 7.0	0.0 - 7.0	5.0 - 8.0
		1.0	8.0 - 17.0	8.0 - 14.0	10.0 - 13.0
		2.0	NaN	NaN	NaN
		3.0	NaN	NaN	NaN
19	Male	0.0	4.0 - 4.0	0.0 - 0.0	8.0 - 8.0
		1.0	13.5 - 13.5	14.5 - 14.5	10.0 - 10.0
20	Male	0.0	NaN	NaN	6.0 - 6.0
		1.0	13.0 - 13.0	12.0 - 12.0	NaN
		3.0	NaN	NaN	NaN
21	Male	0.0	7.5 - 7.5	NaN	NaN
		1.0	NaN	8.5 - 8.5	9.0 - 12.0
		2.0	NaN	NaN	NaN

Age Ranges for each measurement column

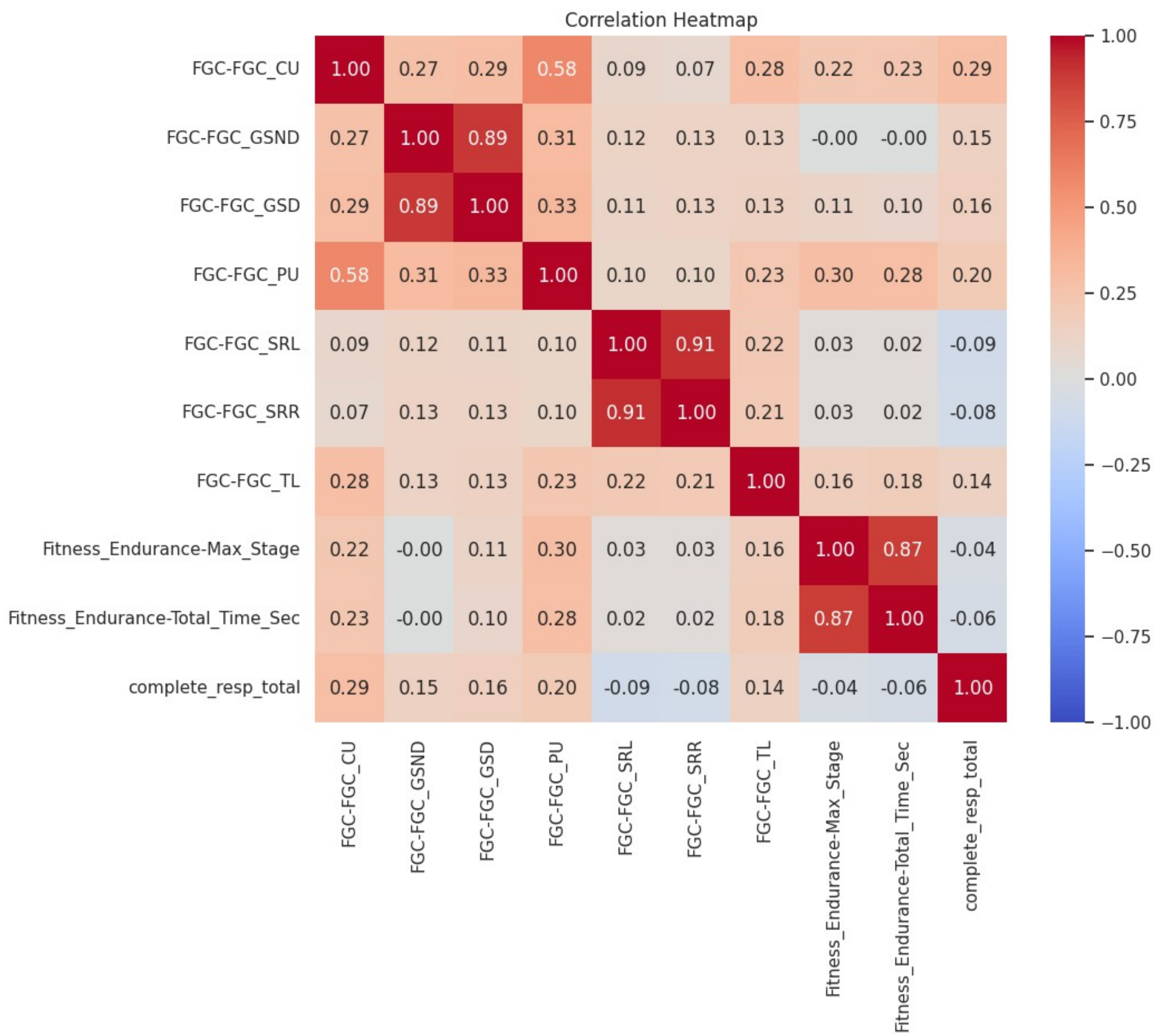
```
age_ranges = []

for measure in measurement_columns:
    valid_rows = train[~train[measure].isna()]

    min_age = valid_rows['Basic_Demos-Age'].min()
    max_age = valid_rows['Basic_Demos-Age'].max()

    age_ranges.append({
        'Measurement': measure,
        'Min Age': min_age,
        'Max Age': max_age
    })

age_ranges_df = pd.DataFrame(age_ranges)
age_ranges_df
```

	Measurement	Min Age	Max Age
0	FGC-FGC_CU	5	21
1	FGC-FGC_GSND	6	21
2	FGC-FGC_GSD	6	21
3	FGC-FGC_PU	5	21
4	FGC-FGC_SRL	5	21
5	FGC-FGC_SRR	5	21
6	FGC-FGC_TL	5	21

In addition, it also doesn't make sense to call this a children's FitnessGram, since participants of almost all ages (5-21) were tested.

Relationships with the target variable (PCIAT_Total for complete PCIAT responses)

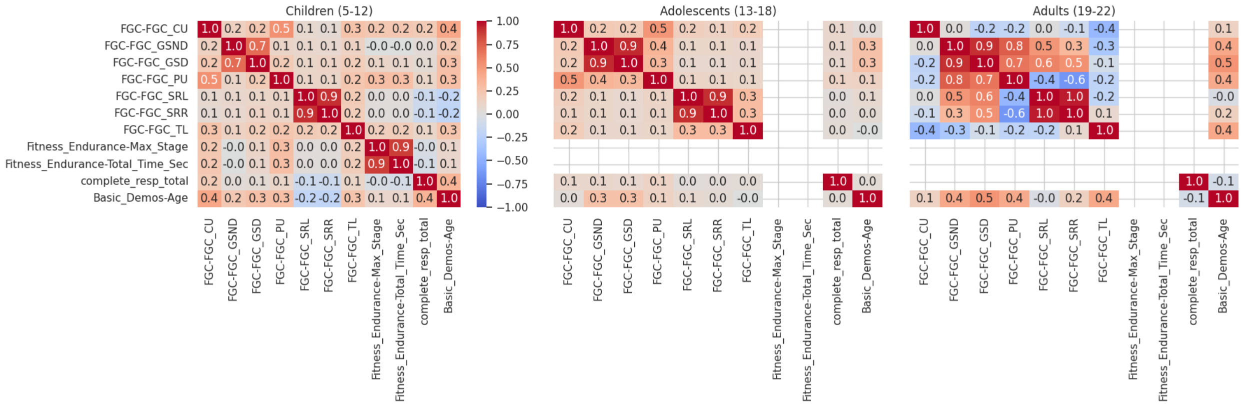
```
cols = [col for col in train.columns if col.startswith('FGC-')
        and 'Zone' not in col and 'Season' not in col]
cols.extend(['Fitness_Endurance-Max_Stage', 'Fitness_Endurance-
Total_Time_Sec'])

data_subset = train[cols + ['complete_resp_total']]

corr_matrix = data_subset.corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f',
vmin=-1, vmax=1)
plt.title('Correlation Heatmap')
plt.show()
```



Let's see how the picture changes when we plot the same thing by age group, and add age to see if the measures still correlate with age.

```
age_groups = train['Age Group'].unique()

fig, axes = plt.subplots(1, 3, figsize=(18, 6), sharey=True)

for i, age_group in enumerate(age_groups):
    group_data = train[train['Age Group'] == age_group]
    corr_matrix = group_data[cols + ['complete_resp_total',
'Basic_Demos-Age']].corr()
    sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.1f',
                vmin=-1, vmax=1, ax=axes[i], cbar=i == 0)
    axes[i].set_title(f'{age_group}')
```

```
plt.tight_layout()
plt.show()
```




```
train[
    (train['Age Group'] == 'Adults (19-22)') &
    (train['complete_resp_total'].notna()) &
    (train[cols].notna().any(axis=1))
][cols + ['complete_resp_total', 'Basic_Demos-Age']]
```

```
      FGC-FGC_CU  FGC-FGC_GSND  FGC-FGC_GSD  FGC-FGC_PU  FGC-
FGC_SRL  \
1483        34.0          52.5         56.8        17.0          13.0


      FGC-FGC_SRR  FGC-FGC_TL  Fitness_Endurance-Max_Stage  \
1483         12.0         6.0                          NaN

      Fitness_Endurance-Total_Time_Sec  complete_resp_total
Basic_Demos-Age
1483                               NaN                  1.0
20
```

- Sleep Disturbance Scale

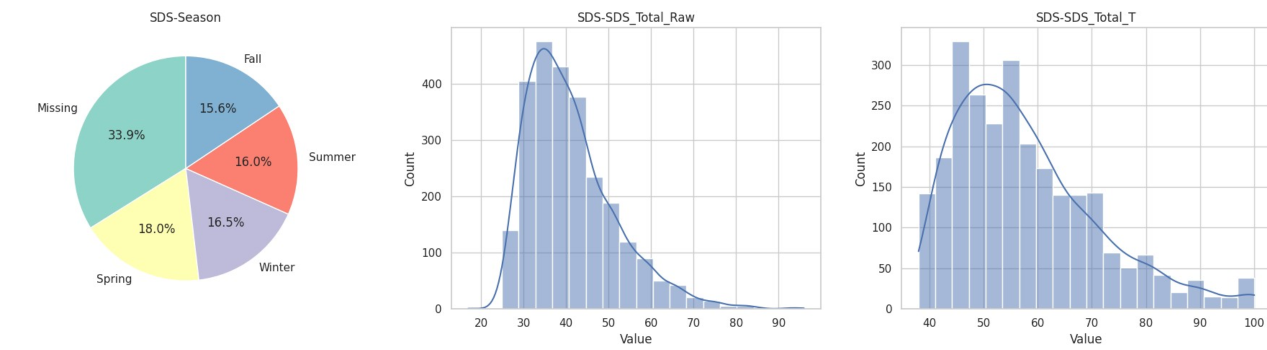
```
groups.get('Sleep Disturbance Scale', [])
```

```
['SDS-Season', 'SDS-SDS_Total_Raw', 'SDS-SDS_Total_T']
```

```
data = train[train['SDS-SDS_Total_Raw'].notnull()]
age_range = data['Basic_Demos-Age']
print(
    f"Age range for participants with SDS-SDS_Total_Raw data:"
    f" {age_range.min()} - {age_range.max()} years"
)
```

```
Age range for participants with SDS-SDS_Total_Raw data: 5 - 22 years
```

```
plt.figure(figsize=(18, 5))

# SDS-Season (Pie Chart)
plt.subplot(1, 3, 1)
sds_season_counts = train['SDS-Season'].value_counts(normalize=True)
plt.pie(
    sds_season_counts,
    labels=sds_season_counts.index,
    autopct='%1.1f%%',
    startangle=90,
    colors=sns.color_palette("Set3")
)
plt.title('SDS-Season')

# SDS-SDS_Total_Raw
plt.subplot(1, 3, 2)
sns.histplot(train['SDS-SDS_Total_Raw'].dropna(), bins=20, kde=True)
plt.title('SDS-SDS_Total_Raw')
plt.xlabel('Value')

# SDS-SDS_Total_T
plt.subplot(1, 3, 3)
sns.histplot(train['SDS-SDS_Total_T'].dropna(), bins=20, kde=True)
plt.title('SDS-SDS_Total_T')
plt.xlabel('Value')

plt.tight_layout()
plt.show()
```




```
calculate_stats(train, ['SDS-SDS_Total_Raw', 'SDS-SDS_Total_T'])
```

```
                    count       mean        std   min   25%   50%
75%  \
SDS-SDS_Total_Raw  2609.0  41.088923  10.427433  17.0  33.0  39.0
46.0
SDS-SDS_Total_T    2606.0  57.763622  13.196091  38.0  47.0  55.0
64.0
```

```
                    max  missing
SDS-SDS_Total_Raw   96.0     1351
SDS-SDS_Total_T    100.0     1354
```

Behavioral (subjective reported)

- Physical Activity Questionnaire

Adolescents

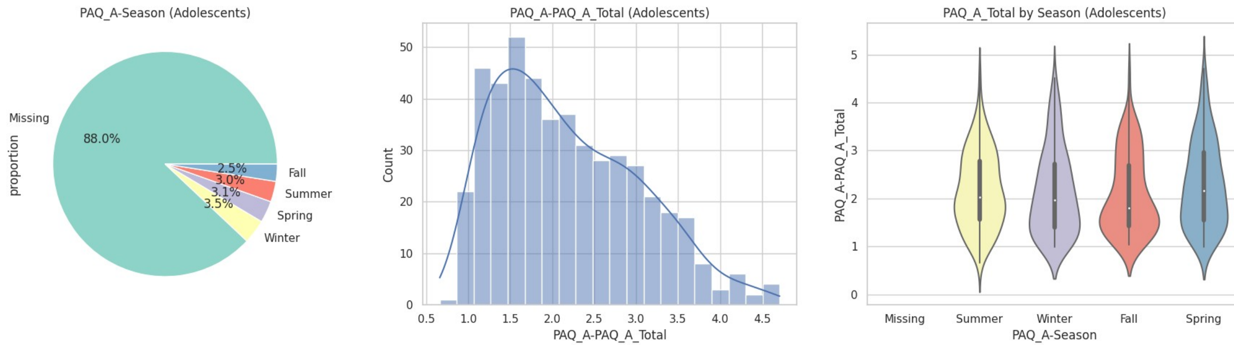
```
groups.get('Physical Activity Questionnaire (Adolescents)', [])
```

```
['PAQ_A-Season', 'PAQ_A-PAQ_A_Total']
```

```
data = train[train['PAQ_A-PAQ_A_Total'].notnull()]
age_range = data['Basic_Demos-Age']
print(
    f"Age range for Adolescents (with PAQ_A_Total data):"
    f" {age_range.min()} - {age_range.max()} years"
)
```

```
Age range for Adolescents (with PAQ_A_Total data): 13 - 18 years
```

```
plt.figure(figsize=(18, 5))

# PAQ_A-Season
plt.subplot(1, 3, 1)
train['PAQ_A-Season'].value_counts(normalize=True).plot.pie(
    autopct='%1.1f%%', colors=plt.cm.Set3.colors
)
plt.title('PAQ_A-Season (Adolescents)')

# PAQ_A-PAQ_A_Total
plt.subplot(1, 3, 2)
sns.histplot(train['PAQ_A-PAQ_A_Total'], bins=20, kde=True)
plt.title('PAQ_A-PAQ_A_Total (Adolescents)')

# PAQ_A_Total by Season
plt.subplot(1, 3, 3)
sns.violinplot(x='PAQ_A-Season', y='PAQ_A-PAQ_A_Total', data=train,
palette="Set3")
plt.title('PAQ_A_Total by Season (Adolescents)')

plt.tight_layout()
plt.show()
```




```
calculate_stats(train, ['PAQ_A-PAQ_A_Total'])
```

```
                   count      mean       std   min   25%   50%   75%  
max  \
PAQ_A-PAQ_A_Total                                                      

PAQ_A-PAQ_A_Total  475.0  2.178853  0.849476  0.66  1.49  2.01  2.78  
4.71

                   missing
PAQ_A-PAQ_A_Total         
PAQ_A-PAQ_A_Total     3485
```

Children

```
groups.get('Physical Activity Questionnaire (Children)', [])
```

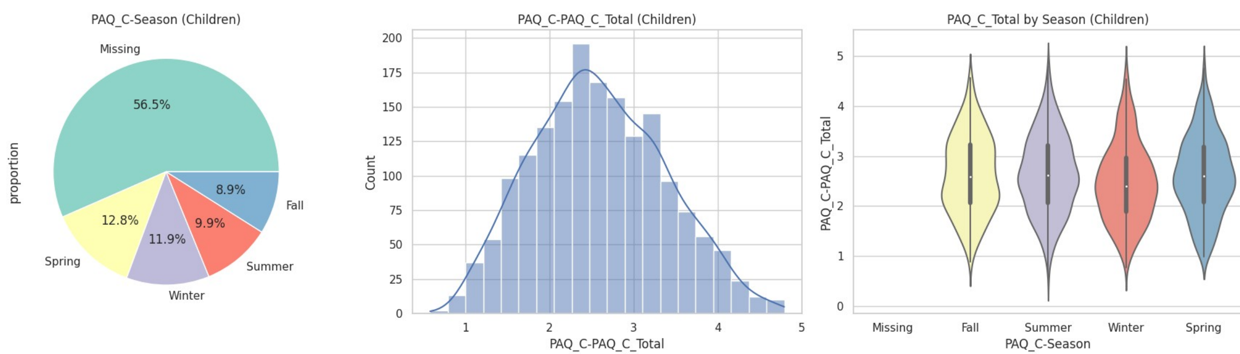
```
['PAQ_C-Season', 'PAQ_C-PAQ_C_Total']
```

```
data = train[train['PAQ_C-PAQ_C_Total'].notnull()]
age_range = data['Basic_Demos-Age']
print(
    f"Age range for Children (with PAQ_C_Total data):"
    f" {age_range.min()} - {age_range.max()} years"
)
```

```
Age range for Children (with PAQ_C_Total data): 7 - 17 years
```

```
plt.figure(figsize=(18, 5))

# PAQ_C-Season
plt.subplot(1, 3, 1)
train['PAQ_C-Season'].value_counts(normalize=True).plot.pie(
    autopct='%1.1f%%', colors=plt.cm.Set3.colors
)
plt.title('PAQ_C-Season (Children)')

# PAQ_C-PAQ_C_Total
plt.subplot(1, 3, 2)
sns.histplot(train['PAQ_C-PAQ_C_Total'], bins=20, kde=True)
```

```
plt.title('PAQ_C-PAQ_C_Total (Children)')

# PAQ_C_Total by Season
plt.subplot(1, 3, 3)
sns.violinplot(x='PAQ_C-Season', y='PAQ_C-PAQ_C_Total', data=train,
palette="Set3")
plt.title('PAQ_C_Total by Season (Children)')

plt.tight_layout()
plt.show()
```




```
calculate_stats(train, ['PAQ_C-PAQ_C_Total'])
```

```
                     count     mean       std   min   25%   50%   75%
max  \
PAQ_C-PAQ_C_Total

PAQ_C-PAQ_C_Total  1721.0  2.58955  0.783937  0.58  2.02  2.54  3.16
4.79

                   missing
PAQ_C-PAQ_C_Total
PAQ_C-PAQ_C_Total     2239
```

Check if any participants have data for both the children's PAQ (PAQ_C) and adolescents' PAQ (PAQ_A) columns

```
paq_columns = [col for col in train.columns if 'PAQ' in col]
train[(train['PAQ_A-PAQ_A_Total'].notnull()) &
      (train['PAQ_C-PAQ_C_Total'].notnull())][
    paq_columns + ['Basic_Demos-Age']
]
```

```
     PAQ_A-Season  PAQ_A-PAQ_A_Total PAQ_C-Season  PAQ_C-
PAQ_C_Total  \
3331       Summer               2.27       Spring               2.32
```

```
      Basic_Demos-Age
3331               13
```

May be it will make sense to combine PAQ_A-PAQ_A_Total and PAQ_C-PAQ_C_Total into a single column and take the average when both values are present.