CS105 Mini Project (Labs 4 - 5)

In this project, we looked to analyze the amount of hours that Students spent playing Video games and watching streams of Video Games. We used the data obtained from our questions, along with supporting data from other questions to formulate a series of hypothesis, assumptions, and tests.

Question 1 - What Data do you have?

Our overall study aimed to primarily ask students the hours they spent playing or watching video games. While this was the primary focus, we asked additional questions:

- How Many Hours do you spend playing games in a week?
- How Many Hours do you spend watching gaming streams in a week?
- What is the name of the game you play the most?

Along with the data from the questions we asked, we also have used additional data from other groups' questions that we have used to find additional correlations.

Question 2 - What would you like to know?

- Is there correlation between the amount of people who play games per week and the amount of people who watch people play games per week.
- Is there correlations in regards to amount of hours spent playing games and other factors?
  - Is there correlation between age and gaming hours?
  - Is there correlation between gender and gaming hours?
  - Is there correlation between streaming videos and gaming hours?
  - Is there correlation between Seating Position in Class and Time Spent Playing Video Games?

We are mainly curious about what behaviors are common amonst people that play games and if those features scale with the amount of time spent on games.

Question 3 - Explain what you are computing

Begin our analysis by getting our raw data from `responses.csv`. Proceed to clean data so that our dataframe, `df` has all the relative information we need:

- Columns were renamed for easier readability.
- Numerical Values converted into float type
- Regex checking to ensure that data fits

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.io as pio
import seaborn as sns
from scipy.stats.stats import pearsonr
```

```python
from scipy.stats import chi2
from scipy.stats import chi2_contingency
import scipy.stats as stats

pio.renderers.default = "plotly_mimetype+notebook"
options(jupyter.plot_mimetypes = c("text/plain", "image/png"))


df = pd.read_csv('responses.csv')

df = df.iloc[:, 74:78]
df = df.rename(columns={'74. How many hours do you play video games in an average week?
df.iloc[:, 0:2] = df.iloc[:, 0:2].replace(to_replace=r'[^\d.]+', value='', regex=True)
df.iloc[:, 0:2] = df.iloc[:, 0:2].replace(to_replace='', value=0)
df.iloc[:, 0:2] = df.iloc[:, 0:2].replace(np.nan, 0)
df.iloc[:, 2:3] = df.iloc[:, 2:3].fillna('None')
df['HourPlayed'] = df['HourPlayed'].astype(float)
df['HourWatched'] = df['HourWatched'].astype(float)

df.head(20)
```

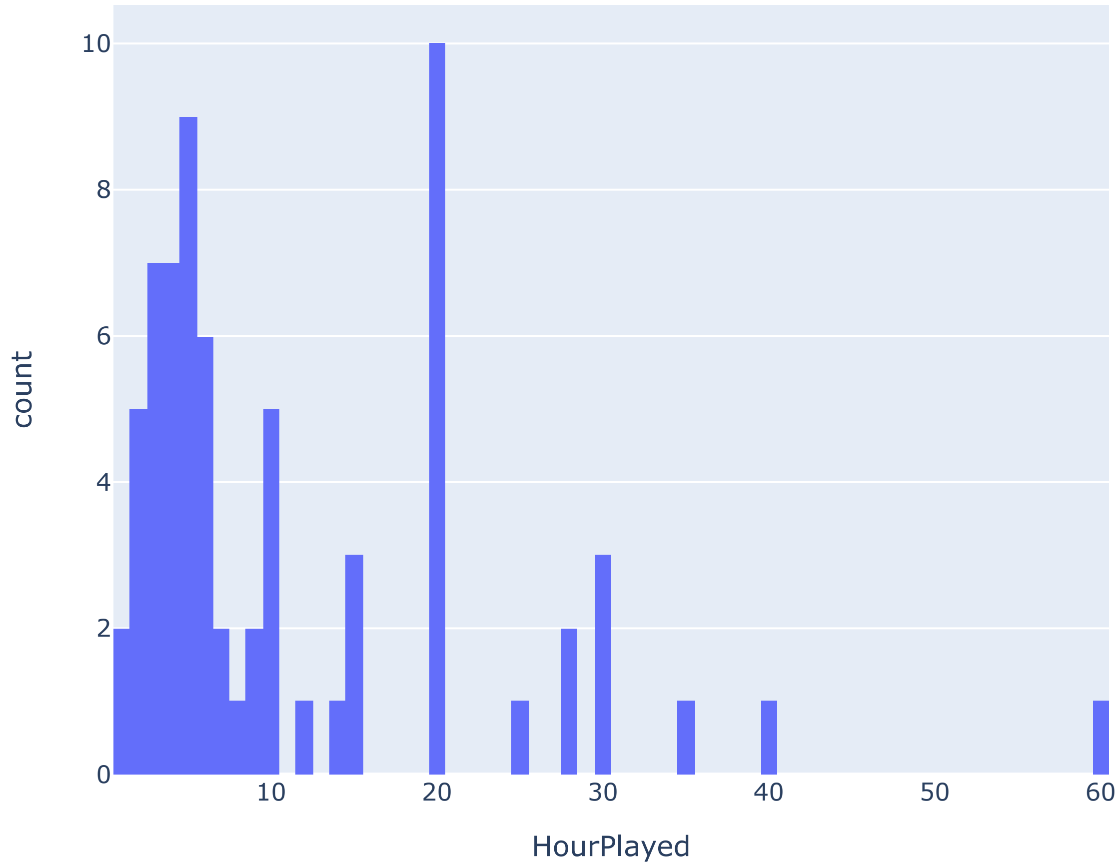
Out[1]:

	HourPlayed	HourWatched	Genre	PlayMost
0	15.0	10.0	FPS, Fighting Games, Gatcha, Single Player Gam...	APEX LEGENDS
1	0.0	0.0	None	NaN
2	20.0	0.0	Gatcha, Single Player Games, RTS, Phone Games	Azur Lane
3	20.0	8.0	FPS, Fighting Games, Gatcha, Single Player Gam...	Tower of Fantasy
4	0.0	0.0	None	NaN
5	0.0	0.0	None	NaN
6	0.0	0.0	None	Na
7	3.0	0.0	MOBA	League of Legends
8	0.0	0.0	Phone Games	Wordle
9	5.0	0.0	Phone Games	Sumikko Farm
10	20.0	0.0	MOBA, FPS, Single Player Games, Phone Games	Genshin impact
11	5.0	1.0	FPS, Single Player Games	Overwatch 2
12	10.0	0.0	Gatcha, Single Player Games, Rhythm Games	Fire Emblem: Three Houses
13	0.0	0.0	MOBA, FPS, Gatcha, MMORPG, Battle Royale, Phon...	Rust
14	10.0	0.0	MOBA, FPS, Gatcha, Single Player Games, MMORPG...	Cookie Run: Kingdom
15	5.0	3.0	MOBA, FPS, Single Player Games, Co-op Games, RTS	Europa Universalis 4
16	4.0	2.0	MOBA, FPS, Fighting Games, Gatcha, Rhythm Games	Fate/Grand Order
17	5.0	0.0	MOBA, Gatcha, Co-op Games	Genshin
18	0.0	0.0	None	NaN
19	3.0	0.0	FPS, Fighting Games, Gatcha, Single Player Gam...	Pokemon

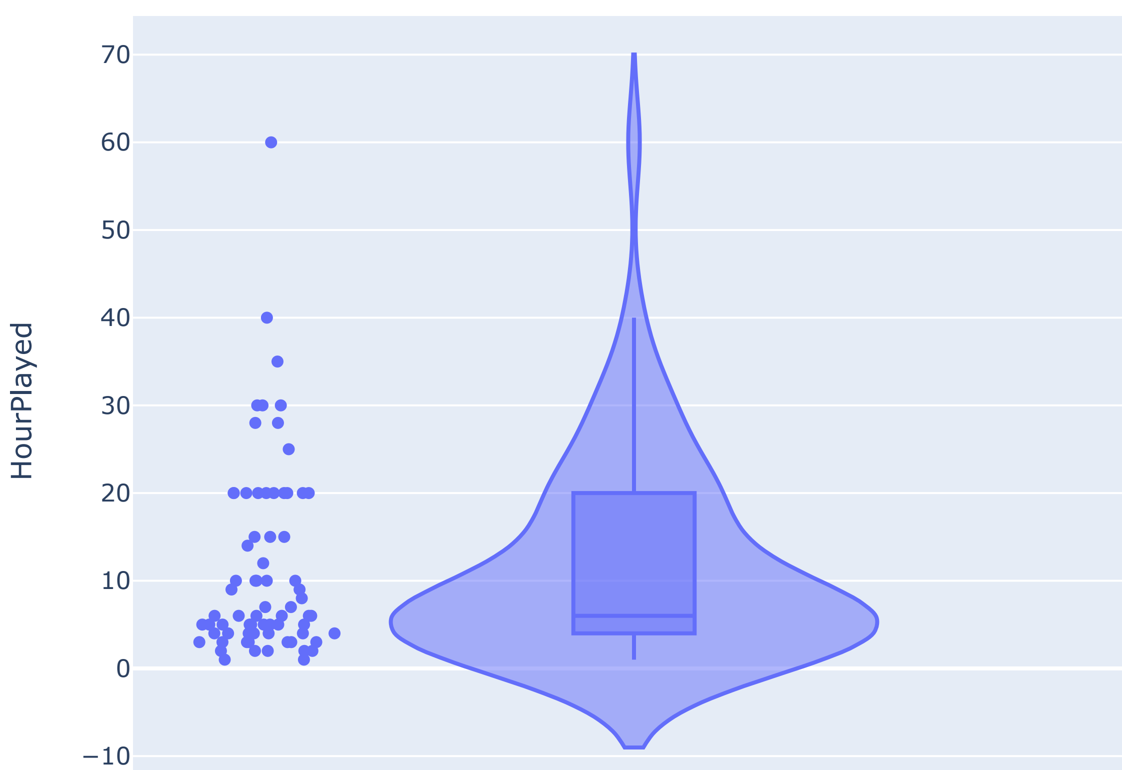
Initial Data Visualization

In [2]:

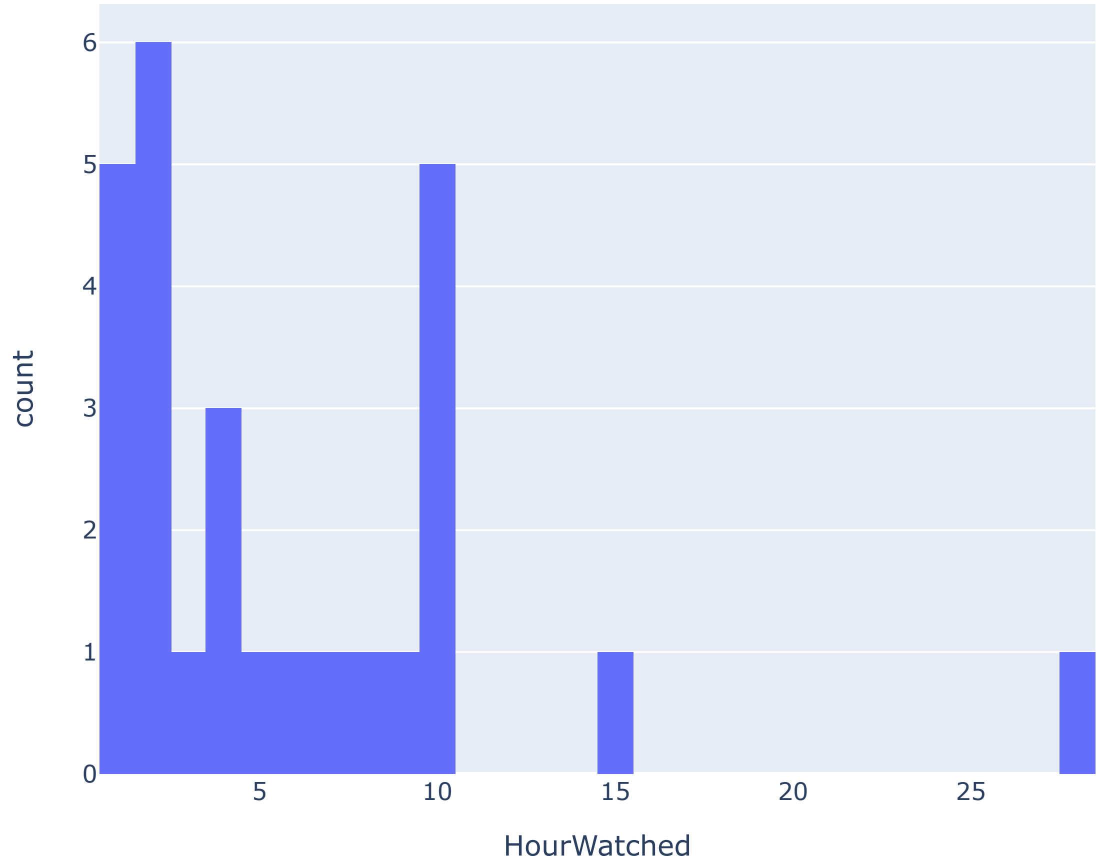
```python
hour_play = df.drop(df[df.HourPlayed == 0].index)
fig = px.histogram(hour_play, x='HourPlayed', nbins=60)
fig.show()
```



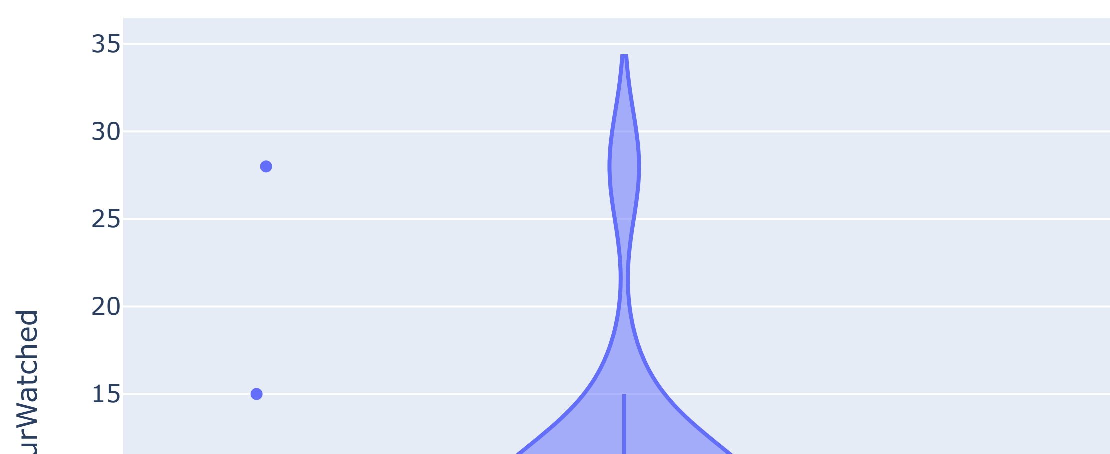
In [3]:
```
violin = df.drop(df[df.HourPlayed == 0].index)
fig = px.violin(violin, y='HourPlayed', box=True, points='all')
fig.show()
```

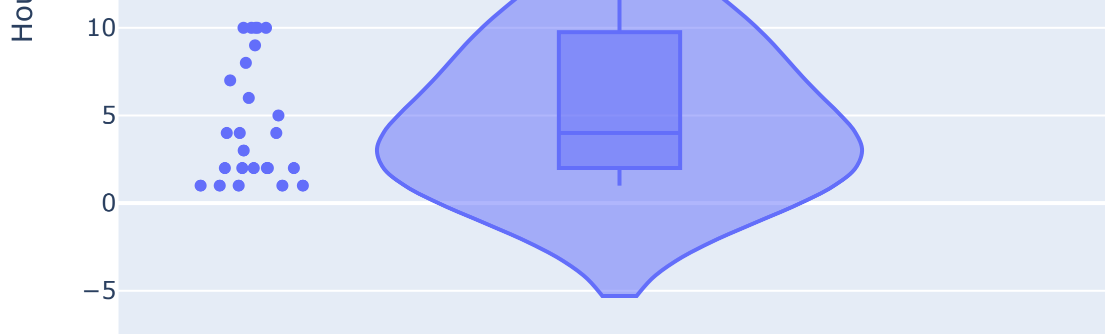


In [4]:
```
hour_watch = df.drop(df[df.HourWatched == 0].index)
fig = px.histogram(hour_watch, x='HourWatched', nbins=30)
fig.show()
```



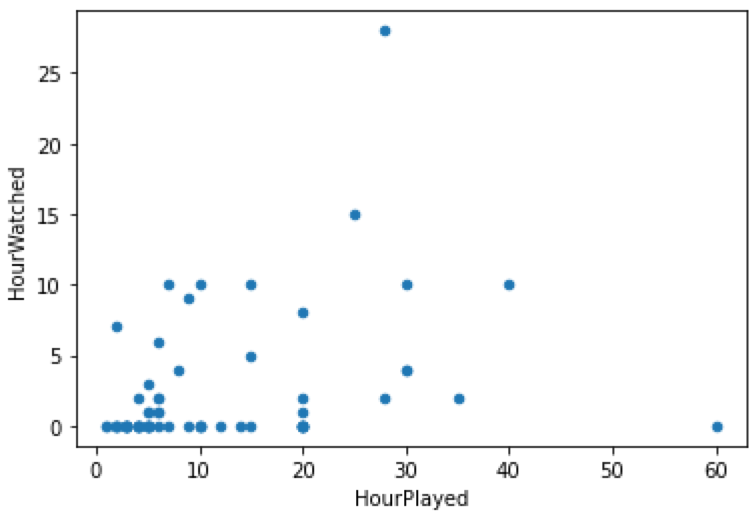
In [5]:
```
violin = df.drop(df[df.HourWatched == 0].index)
fig = px.violin(violin, y='HourWatched', box=True, points='all')
fig.show()
```





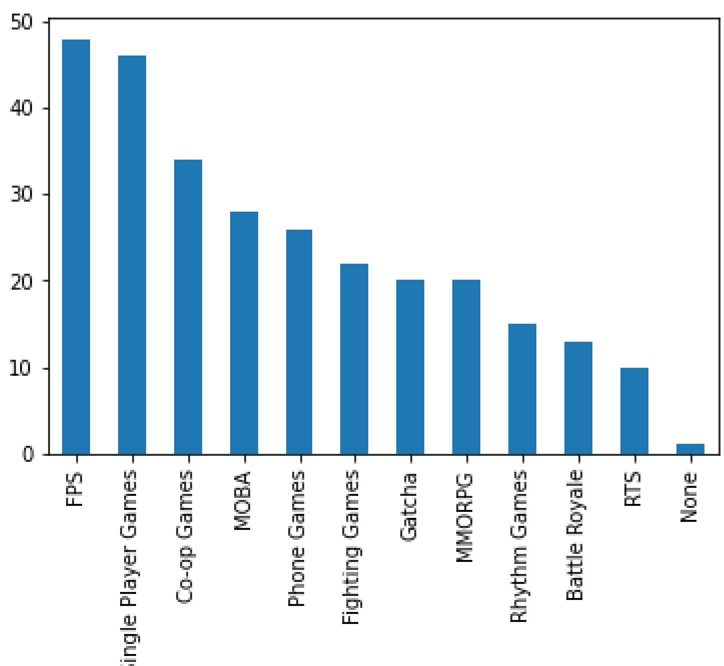
In [6]:
```
df = df.drop(df[df.HourPlayed == 0].index)
df.plot.scatter(x="HourPlayed", y="HourWatched")
```

Out[6]: <AxesSubplot:xlabel='HourPlayed', ylabel='HourWatched'>



In [7]:
```
genre_count = df['Genre'].astype(str).str.split(', ').explode().value_counts()
genre_count.plot(kind='bar')
```

Out[7]: <AxesSubplot:>



Correlation between time spent per week streaming videos (YouTube, Netflix, etc.) and amount of time per week spent playing video games

In [8]:
```
jack_df = pd.read_csv('responses.csv')
streaming = jack_df.iloc[:, 73]
gender = jack_df.iloc[:, 3]
jack_df = jack_df.iloc[:, 74:78]
jack_df = jack_df.rename(columns={'74. How many hours do you play video games in an aver
jack_df.iloc[:, 0:2] = jack_df.iloc[:, 0:2].replace(to_replace=r'[^\d.]+', value='', reg
jack_df.iloc[:, 0:2] = jack_df.iloc[:, 0:2].replace(to_replace='', value=0)
jack_df.iloc[:, 0:2] = jack_df.iloc[:, 0:2].replace(np.nan, 0)
jack_df.iloc[:, 2:3] = jack_df.iloc[:, 2:3].fillna('None')

jack_df['Streaming'] = streaming.replace(to_replace=r'[^\d.]+', value='', regex=True).re
jack_df['Gender'] = gender
jack_df.head(20)
```

Out[8]:

	HourPlayed	HourWatched	Genre	PlayMost	Streaming	Gender
0	15	10	FPS, Fighting Games, Gatcha, Single Player Gam...	APEX LEGENDS	15.0	Male
1	0	0	None	NaN	14.0	Female
2	20	0	Gatcha, Single Player Games, RTS, Phone Games	Azur Lane	20.0	Male
3	20	8	FPS, Fighting Games, Gatcha, Single Player Gam...	Tower of Fantasy	15.0	Male
4	0	0	None	NaN	5.0	Female
5	0	0	None	NaN	4.0	Female
6	0	0	None	Na	5.0	Female
7	3	0	MOBA	League of Legends	3.0	Male
8	0	0	Phone Games	Wordle	10.0	Female
9	5	0	Phone Games	Sumikko Farm	22.0	Female
10	20	0	MOBA, FPS, Single Player Games, Phone Games	Genshin impact	40.0	Male
11	5	1	FPS, Single Player Games	Overwatch 2	10.0	Male
12	10	0	Gatcha, Single Player Games, Rhythm Games	Fire Emblem: Three Houses	25.0	Male
13	0	0	MOBA, FPS, Gatcha, MMORPG, Battle Royale, Phon...	Rust	10.0	Male
14	10	0	MOBA, FPS, Gatcha, Single Player Games, MMORPG...	Cookie Run: Kingdom	10.0	Male
15	5	3	MOBA, FPS, Single Player Games, Co-op Games, RTS	Europa Universalis 4	20.0	Male
16	4	2	MOBA, FPS, Fighting Games, Gatcha, Rhythm Games	Fate/Grand Order	84.0	Male
17	5	0	MOBA, Gatcha, Co-op Games	Genshin	3.0	Male
18	0	0	None	NaN	1.0	Female
19	3	0	FPS, Fighting Games, Gatcha, Single Player Gam...	Pokemon	10.0	Male

Hypothesis: The time spent per week streaming videos such as youtube or netflix will correlate with the amount of time per week spent playing video games.

Reasoning: We think this is because people that play video games will also watch video games, thus increasing their time spent streaming videos. If this is true, we expect the correlation between hours spend watching games and hours playing games to be similar to the correlation between hours spent streaming videos and hours spent watching because there is an overlap between time spent streaming videos and time spent watching games.

Therefore to test this hypothesis we will use the pearson correlation test because it checks for correlation between continuous numeric variables, which is applicable here as all variables are measured in time.

We will be using the pearson correlation test on hours watching video games and hours playing video games, hours streaming videos and playing video games, and finally hours watching video games and hours streaming videos.

In [9]:
```
jack_df['HourPlayed']=jack_df['HourPlayed'].astype('float')
jack_df['HourWatched']=jack_df['HourWatched'].astype('float')
impdf = jack_df.dropna(subset = ['Streaming'])
(hpsr, hpsp) = pearsonr(impdf['HourPlayed'], impdf['Streaming'])
(hpwr, hpwp) = pearsonr(impdf['HourPlayed'], impdf['HourWatched'])
(wsr, wsp) = pearsonr(impdf['HourWatched'], impdf['Streaming'])

print('Pearson Correlation Coefficient between hours playing video games per week and ho
      round(hpsr, 4))
print('P-value for that correlation: ', f'{hpsp:.5f}')
print('Pearson Correlation Coefficient between hours playing video games per week and ho
     round(hpwr, 4))
print('P-value for that correlation: ', f'{hpwp:.5f}')
print('Pearson Correlation Coefficient between hours watching video games per week and h
     round(wsr, 4))
print('P-value for that correlation: ', round(wsp, 5))
```

```
Pearson Correlation Coefficient between hours playing video games per week and hours str
eaming videos per week:  0.4314
P-value for that correlation:  0.00001
Pearson Correlation Coefficient between hours playing video games per week and hours wat
ching video games per week:  0.4227
P-value for that correlation:  0.00001
Pearson Correlation Coefficient between hours watching video games per week and hours st
reaming videos per week:  0.3703
P-value for that correlation:  0.00013
```

Conclusion: It appears that our hypothesis was correct!

Notice the correlation between hours playing games and hours streaming videos is similar to the correlation between hours playing video games and hours watching video games. This means that hours playing games is about equal in predicting the hours spent streaming videos and also hours spent watching video games. This lines up with our hypothesis, I would argue that this is due to the overlap between watching games and streaming videos.

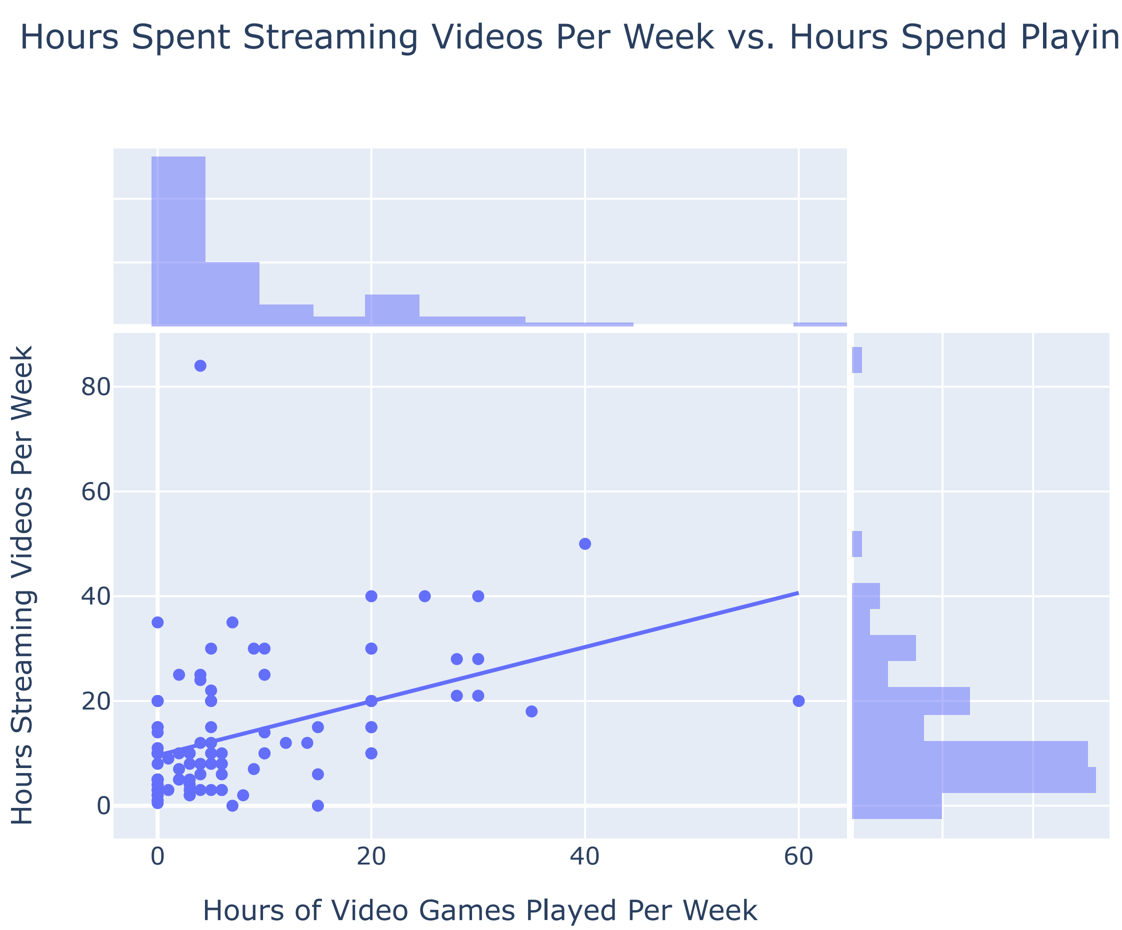
Since the correlation coefficients of the two correlations are about `0.43`, we argue that there is a weak-moderate correlation between the hours playing video games to both hours streaming videos and hours watching video games.

The final part of this is to test whether the hours spent watching video games is correlated to the hours spent streaming videos. We got a pearson correlation coefficient of `0.37`, which is lower than the previous coefficients. This means that the overlap between the hours streaming and hours watching video games is not more significant than the fact that people who play more video games also stream more videos in general.

This would mean that people who play more video games also stream more videos, which could be used to imply that people who play more video games spend a lot more time on their electronic devices as they spend more time watching videos and playing video games.

Of course this does not guarantee this, but from the data I would expect this to be true. To test further into this we would need data on how long everyone spends on electronic devices per week and take the correlations between that and hours playing games per week.

In [10]:
```
import plotly.express as px

fig = px.scatter(impdf, x="HourPlayed", y="Streaming", marginal_x="histogram", marginal_
    "HourPlayed": "Hours of Video Games Played Per Week",
    "Streaming": "Hours Streaming Videos Per Week"
}, title = "Hours Spent Streaming Videos Per Week vs. Hours Spend Playing Video Games Pe
fig.show()
```

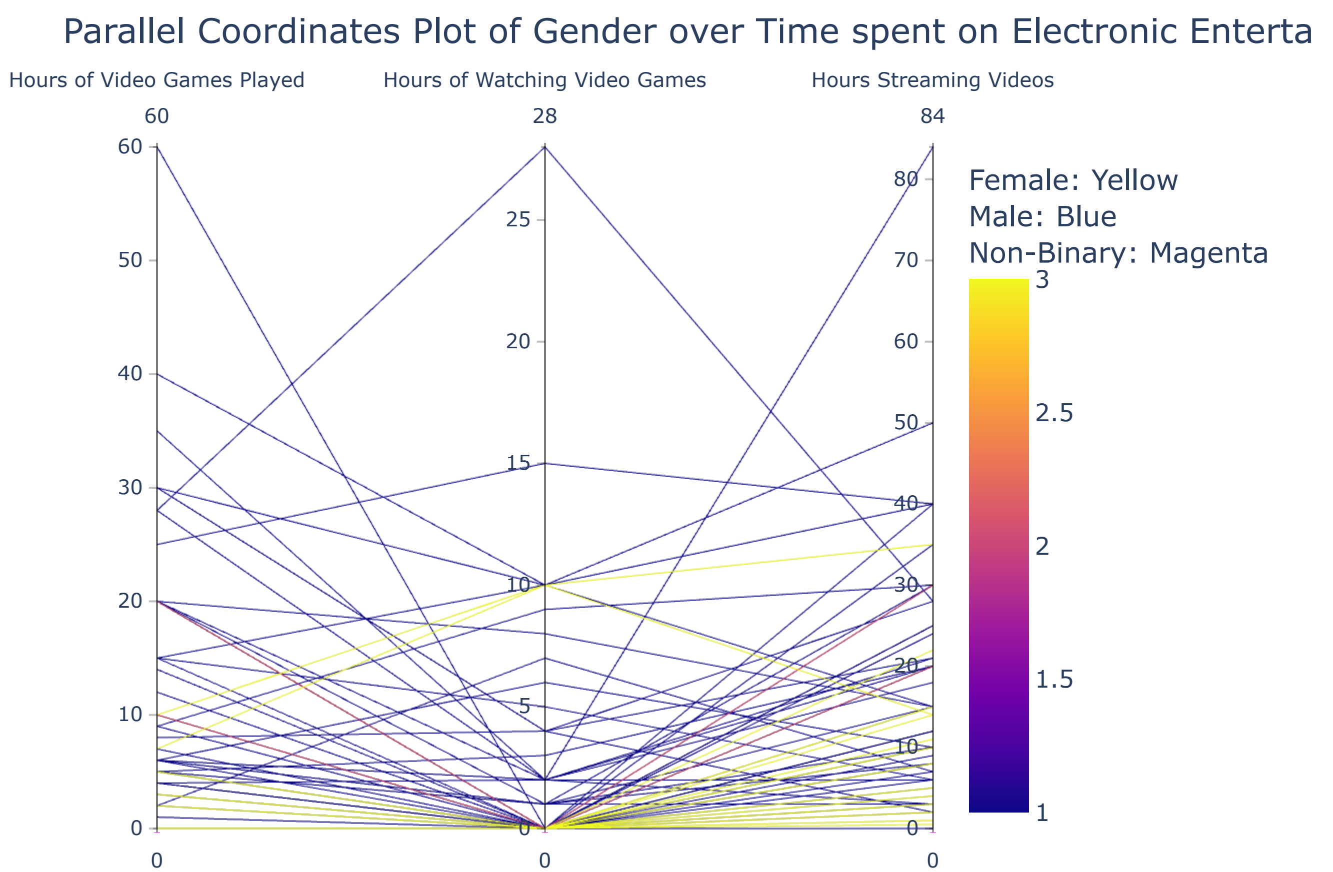


This visualization shows the distribution of both datasets whilst also showing the scatterplot of the data and the trendline. This visualization is meant to show that both datasets are skewed to the right because from the data we collected, most people did not watch or play that many games.

This visualization is being used to show how our data is not entirely evenly distributed so the results may be skewed as well when calculating correlation coefficients.

In [11]:
```
impdf['Gender']=impdf['Gender'].replace(to_replace='Male', value=1).replace(to_replace='
fig = px.parallel_coordinates(impdf, color='Gender',
                              dimensions=['HourPlayed', 'HourWatched', 'Streaming'], lab
    "HourPlayed": "Hours of Video Games Played",
    "Streaming": "Hours Streaming Videos",
    "HourWatched": "Hours of Watching Video Games",
    "Gender": "Female: Yellow<br>Male: Blue<br>Non-Binary: Magenta"
}, title="Parallel Coordinates Plot of Gender over Time spent on Electronic Entertainmen
fig.show()
```

```
C:\Users\chai\AppData\Local\Temp\ipykernel_33672\3747005512.py:1: SettingWithCopyWarnin
g:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
```



This visualization is a little more difficult to read, but it is a parallel coordinates plot between hours playing games, hours watching video games, and hours streaming videos. The different colors are the genders with yellow being female, blue being male, and magenta being non-binary.

Focus on the colors, you will see that almost all of the yellow lines converge to 0 in the games watched column. On the other hand the blue lines are all over the place. This shows that while the male students consume gaming content when they play games, it appears that even if female students play games, on average they do not watch any gaming streams. This does not mean that female students do not stream videos though, from the graph if you see the streaming videos column, the female students diverge from 0 into different values ranging from 0-35ish hours per week.

There are the two exceptions that watch a fair bit of games, but almost every female student that plays games does not watch any games. Also notice how most female students play much less games than their male counterparts. From the female students that play video games, they are all under the 10 hour mark per week.

Male students on the other hand range from the entire spectrum.

This graph although hard to read, highlights some aspects of the data in relation to gender particularly well as pointed out above.

Testing Correlation

In [12]:

```
#Creating chi square test for bins of values to turn numerical data into categorical dat
#Bins: 0, 1-5, 6-10, 11-15, 16-20, 21-25, 26-30, 31-35, ... 55-60

bins = range(-10,100,10)
jack_df = jack_df.dropna(subset=['HourPlayed', 'HourWatched'])
jack_df['HourPlayedBins'] = pd.cut(jack_df['HourPlayed'],bins)
jack_df['HourWatchedBins'] = pd.cut(jack_df['HourWatched'],bins)

print(jack_df['HourPlayedBins'])
```

```
0       (10, 20]
1       (-10, 0]
2       (10, 20]
3       (10, 20]
4       (-10, 0]
          ...
105     (-10, 0]
106      (0, 10]
107     (20, 30]
108     (20, 30]
109     (10, 20]
Name: HourPlayedBins, Length: 110, dtype: category
Categories (10, interval[int64, right]): [(-10, 0] < (0, 10] < (10, 20] < (20, 30] ...
(50, 60] < (60, 70] < (70, 80] < (80, 90]]
```

In [13]:

```
print(jack_df['HourWatchedBins'])
```

```
0        (0, 10]
1       (-10, 0]
2       (-10, 0]
3        (0, 10]
4       (-10, 0]
          ...
105     (-10, 0]
106     (-10, 0]
107      (0, 10]
108      (0, 10]
109      (0, 10]
Name: HourWatchedBins, Length: 110, dtype: category
Categories (10, interval[int64, right]): [(-10, 0] < (0, 10] < (10, 20] < (20, 30] ...
(50, 60] < (60, 70] < (70, 80] < (80, 90]]
```

In [14]:

```
chitable = pd.DataFrame()
chitable['HourPlayedBins'] = jack_df['HourPlayedBins']
chitable['HourWatchedBins'] = jack_df['HourWatchedBins']
chitable['HourWatched'] = jack_df['HourWatched']
chitable.pivot_table(index='HourPlayedBins', columns='HourWatchedBins', aggfunc='count')
```

```
contingency = pd.crosstab(chitable['HourPlayedBins'], chitable['HourWatchedBins'])
contingency
```

Out[14]:

HourWatchedBins HourPlayedBins	(-10, 0]	(0, 10]	(10, 20]	(20, 30]
(-10, 0]	40	0	0	0
(0, 10]	32	14	0	0
(10, 20]	10	5	0	0
(20, 30]	0	4	1	1
(30, 40]	0	2	0	0
(50, 60]	1	0	0	0

In [15]:

```
c, p, dof, expected = chi2_contingency(contingency)
print(p)
```

```
2.3215745527735668e-08
```

Above I computed the chi square test for HourWatched vs. HourPlayed by turning each of the numeric variables into bins first to make the variables categorical. I then applied the chi square test to get a p-value of 2.32e-08. The null hypothesis in this case is that the hours playing games per week and the hours watching gaming streams per week are independent. The P-value represents the probability that this is the case. Since the probability is so low, I reject the null hypothesis and state that the hours playing games per week are correlated to the hours watching gaming streams per week.

Correlation Between Seating Position in Class and Time Spent Playing Video Games

Hypothesis: The further back you sit in a classroom, the more time you spend playing video games.

Test: We will calculate the correlation coefficient to determine if there is a correlation between time spent playing video games, and seating position in class.

In [16]:

```
seating_df = pd.read_csv('responses.csv')
seating_df = seating_df.iloc[:, 41:42]
seating_df = seating_df.rename(columns={'41. How close do you sit to the front of class?
seating_df = pd.concat([seating_df, df], axis=1)
seating_df = seating_df.iloc[:, 0:2]
df['HourPlayed'] = df['HourPlayed'].astype(float)
#seating_df = seating_df.drop(seating_df[seating_df.HourPlayed == 0].index)
seating_df.head()
```

Out[16]:

	Seating	HourPlayed
0	3.0	15.0
1	2.0	NaN
2	3.0	20.0
3	3.0	20.0
4	2.0	NaN

In [17]:

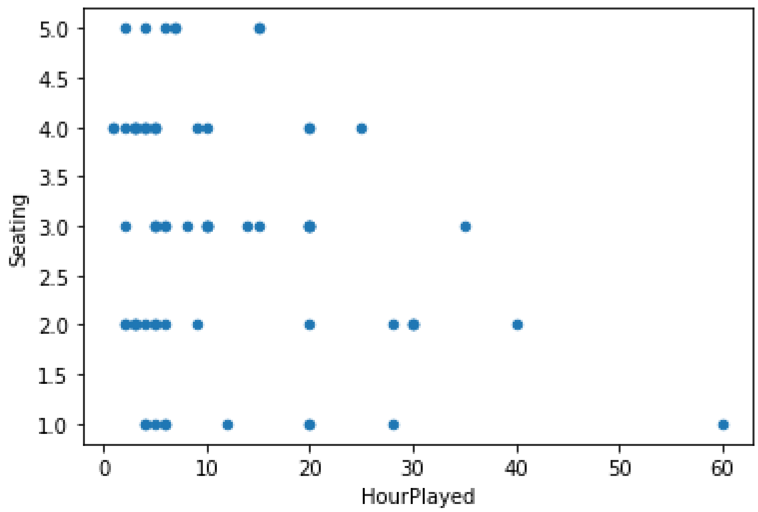
```
r = seating_df['Seating'].corr(seating_df['HourPlayed'])
r
```

Out[17]: -0.28559551117436194

Results: There is a negative correlation of -0.18. As time spent playing increases, seating position decreases. This does not match the hypothesis. We thought people who sit in the back of classrooms tend to play more video games, but the data does not corroborate this.

In [18]:
```
seating_df.plot.scatter(x='HourPlayed', y='Seating')
```

Out[18]: <AxesSubplot:xlabel='HourPlayed', ylabel='Seating'>



Correlation between age and time spent playing Video Games

Hypothesis: Younger College Students spent hours per week playing video games.

In [19]:
```
jason_df = pd.read_csv("responses.csv")

jason_df = jason_df.iloc[:, 74:78]
jason_df = jason_df.rename(columns={'74. How many hours do you play video games in an av
jason_df.iloc[:, 0:2] = jason_df.iloc[:, 0:2].replace(to_replace=r'[^\d.]+', value='', r
jason_df.iloc[:, 0:2] = jason_df.iloc[:, 0:2].replace(to_replace='', value=0)
jason_df.iloc[:, 0:2] = jason_df.iloc[:, 0:2].replace(np.nan, 0)
jason_df.iloc[:, 2:3] = jason_df.iloc[:, 2:3].fillna('None')

age_df = pd.read_csv('responses.csv')
age_df = age_df.iloc[:, 2:3]
age_df = age_df.rename(columns={'2. What is your age?' : 'age'})
age_df = pd.concat([age_df, df], axis=1)
age_df = age_df.iloc[:, 0:3]
jason_df['HourPlayed'] = jason_df['HourPlayed'].astype(float)
jason_df['HourWatched'] = jason_df['HourWatched'].astype(float)
#combine data set from responses, and compare with HourPlayed and HourWatched
```

Within the age, there was one entry (18-21), that was solved by just taking 20 from the average

In [20]:
```
age_df.iloc[47:48,0:1] = age_df.iloc[47:48,0:1].replace('18-21','20')
```

In [21]:
```
age_df.iloc[:, 0:3] = age_df.iloc[:, 0:3].replace(np.nan, 0)
age_df['age'] = age_df['age'].astype(float)
age_df['HourWatched'] = age_df['HourWatched'].astype(float)
age_df['HourPlayed'] = age_df['HourPlayed'].astype(float)
age_df
```

Out[21]:

	age	HourPlayed	HourWatched

0	22.0	15.0	10.0
1	22.0	0.0	0.0
2	27.0	20.0	0.0
3	24.0	20.0	8.0
4	40.0	0.0	0.0
...	...	...	...
105	22.0	0.0	0.0
106	23.0	5.0	0.0
107	19.0	30.0	4.0
108	21.0	28.0	2.0
109	19.0	20.0	1.0

110 rows × 3 columns

We want to change the Age Column into our index

In [22]:

```
new_age_df = age_df.set_index('age')    #making age as index
new_age_df
```

Out[22]:

	HourPlayed	**HourWatched**
age		
22.0	15.0	10.0
22.0	0.0	0.0
27.0	20.0	0.0
24.0	20.0	8.0
40.0	0.0	0.0
...	...	...
22.0	0.0	0.0
23.0	5.0	0.0
19.0	30.0	4.0
21.0	28.0	2.0
19.0	20.0	1.0

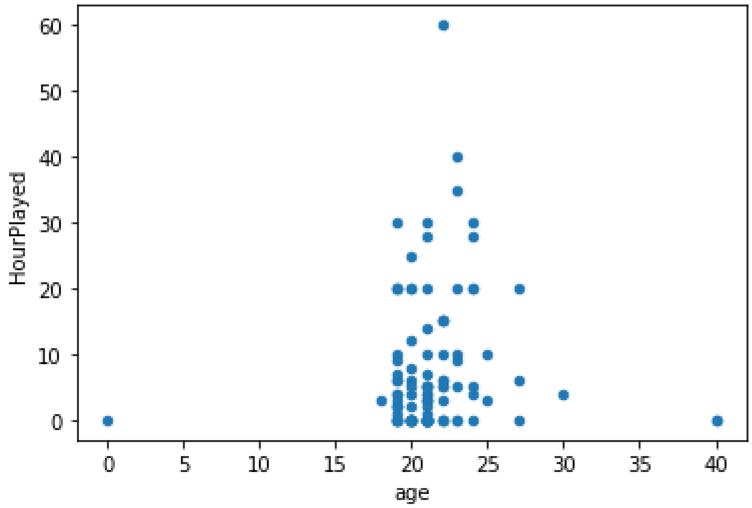
110 rows × 2 columns

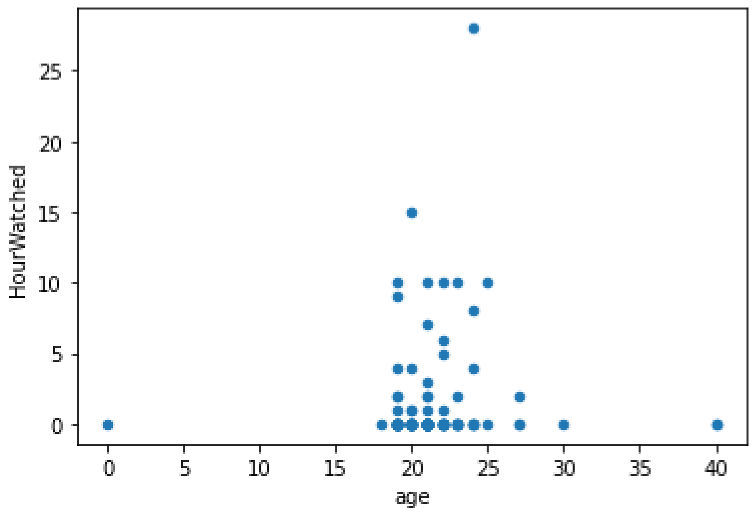
In [23]:

```
age_df.plot.scatter(x="age", y = "HourPlayed")
age_df.plot.scatter(x="age", y = "HourWatched")
```

Out[23]:

```
<AxesSubplot:xlabel='age', ylabel='HourWatched'>
```





By oberserving the previous graph, we can see that most of the dot are concentrate between age 18-24. They look like that age is directly related to `HourWatched` and `HourPlayed`, but since our data set is taken among 3 CS classes and we are mostly 18-24 years old so the case does not work as they have shown.

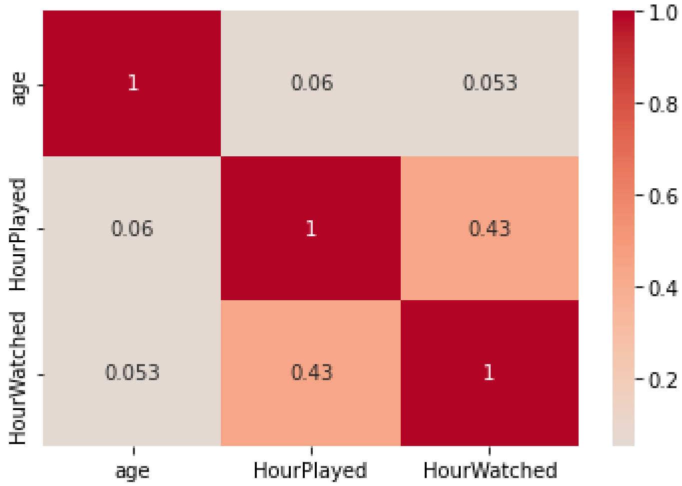
In [24]:
```
h = age_df[["age","HourPlayed","HourWatched"]].corr()
h
```

Out[24]:

	age	HourPlayed	HourWatched
age	1.000000	0.060016	0.053445
HourPlayed	0.060016	1.000000	0.433021
HourWatched	0.053445	0.433021	1.000000

In [25]:
```
sns.heatmap(h,center=0, cmap = "coolwarm", annot=True)
```

Out[25]:
```
<AxesSubplot:>
```



We can see the correlations between `age` and `HourWatch`, `HourPlayed` are around `0.05`, which indicates a weak positive relationship.

Conducting Chi-Squared Test on Data

The chi-squared test is a hypothesis test used to determine whether there is any significant association between two catergorical variables in the data. In our case, we would like to see if there is any significance between `HourWatched` and `HourPlayed`. Before we can proceed into testing, we must first develop our two hypothesis:

H0: There is **no relationship** between the two variables, and our data is independent

H1: There **is a relationship between the two variables**, and our data is dependent on the other.

In [26]:
```
age_df
```

Out[26]:

	age	HourPlayed	HourWatched
0	22.0	15.0	10.0
1	22.0	0.0	0.0
2	27.0	20.0	0.0
3	24.0	20.0	8.0
4	40.0	0.0	0.0
...	...	...	...
105	22.0	0.0	0.0
106	23.0	5.0	0.0
107	19.0	30.0	4.0
108	21.0	28.0	2.0
109	19.0	20.0	1.0

110 rows × 3 columns

In [27]:
```
Playhours_count = age_df.iloc[:,0:2] #chi-square on HourPlayed and age
Playhours_count.loc['col_total'] = Playhours_count.sum(axis=0)
Playhours_count['row_total'] = Playhours_count.sum(axis=1)
Playhours_count
```

```
C:\Users\chai\AppData\Local\Temp\ipykernel_33672\4184475003.py:2: SettingWithCopyWarnin
g:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy

C:\Users\chai\AppData\Local\Temp\ipykernel_33672\4184475003.py:3: SettingWithCopyWarnin
g:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
```

Out[27]:

	age	HourPlayed	row_total
0	22.0	15.0	37.0
1	22.0	0.0	22.0
2	27.0	20.0	47.0
3	24.0	20.0	44.0
4	40.0	0.0	40.0
...	...	...	...
106	23.0	5.0	28.0
107	19.0	30.0	49.0
108	21.0	28.0	49.0
109	19.0	20.0	39.0
col_total	2348.0	809.0	3157.0

111 rows × 3 columns

In [28]:

```
expectPlayHour = np.outer(Playhours_count["row_total"][0:111], Playhours_count.loc["col_
expectedPlayHour = pd.DataFrame(expectPlayHour)
expectedPlayHour.columns = ['age','HourPlayed']
expectedPlayHour
```

Out[28]:

	age	HourPlayed
0	27.319497	9.412893
1	16.244025	5.596855
2	34.703145	11.956918
3	32.488050	11.193711
4	29.534591	10.176101
...	...	...
106	20.674214	7.123270
107	36.179874	12.465723

108	36.179874	12.465723
109	28.796226	9.921698
110	2331.017610	803.148742

111 rows × 2 columns

In [29]:
```
chi_squared_stat1 = (((age_df - expectedPlayHour)**2)/expectedPlayHour).sum().sum()
chi_squared_stat1
```

Out[29]:
```
830.3359060367851
```

In [30]:
```
critical_value = chi2.ppf(q=0.999, df=110)
print("Critical Value:",critical_value)

p_value = 1 - (chi2.cdf(x=chi_squared_stat1, df=110))
print("P Value:", p_value)
```

```
Critical Value: 161.58073982908158
P Value: 0.0
```

In [31]:
```
Watchhours_count = age_df.loc[:,('age','HourWatched')] #chi-square on HourWatch and age
Watchhours_count.loc['col_total'] = Watchhours_count.sum(axis=0)
Watchhours_count['row_total'] = Watchhours_count.sum(axis=1)
Watchhours_count
```

Out[31]:

	age	HourWatched	row_total
0	22.0	10.0	32.0
1	22.0	0.0	22.0
2	27.0	0.0	27.0
3	24.0	8.0	32.0
4	40.0	0.0	40.0
...	...	...	...
106	23.0	0.0	23.0
107	19.0	4.0	23.0
108	21.0	2.0	23.0
109	19.0	1.0	20.0
col_total	2348.0	160.0	2508.0

111 rows × 3 columns

In [32]:
```
expectWatchHour = np.outer(Watchhours_count["row_total"][0:111], Watchhours_count.loc["c
expectedWatchHour = pd.DataFrame(expectWatchHour)
expectedWatchHour.columns = ['age','HourWatched']
expectedWatchHour
```

Out[32]:

	age	HourWatched
0	29.686290	2.022916
1	20.409324	1.390755
2	25.047807	1.706835

3	29.686290	2.022916
4	37.107863	2.528645
...	...	...
106	21.337021	1.453971
107	21.337021	1.453971
108	21.337021	1.453971
109	18.553931	1.264322
110	2326.662979	158.546029

111 rows × 2 columns

In [33]:
```
chi_squared_stat2 = (((age_df - expectedWatchHour)**2) / expectedWatchHour).sum().sum()
chi_squared_stat2
```

Out[33]:
```
666.0874246473343
```

In [34]:
```
critical_value = chi2.ppf(q=0.999, df=110)
print("Critical Value:",critical_value)

p_value = 1 - (chi2.cdf(x=chi_squared_stat2, df=110))
print("P Value:", p_value)
```

```
Critical Value: 161.58073982908158
P Value: 0.0
```

Since both of the p value from test `Age` to `HourWatch` and test `Age` to `HourPlayed` are 0, which indicates that we should reject the null hypothesis. Age is independent to HourWatched and HourPlayed.

Correlation between Time Spent Playing Video Games and Time Spent Socializing with friends on Campus.

Hypothesis: The more time a college student spends playing video games, the less time they spend socializing with friends on campus.

Null Hypothesis: The time a college student spends playing video games does not have an effect on the time they socialize with friends on campus.

In [35]:
```
ayu_df = pd.read_csv('responses.csv')
ayu_df = ayu_df.iloc[:, [74, 79]]

ayu_df = ayu_df.rename(columns={'74. How many hours do you play video games in an averag
ayu_df = ayu_df.rename(columns={'79. From the people that you have met on campus, how ma
ayu_df = ayu_df.apply(pd.to_numeric, errors='coerce').dropna()
ayu_df['Hours Spent Socializing'] = ayu_df['Hours Spent Socializing'].astype(float)
ayu_df['Hours Playing Video Games'] = ayu_df['Hours Playing Video Games'].astype(float)
ayu_df.head(5)
```

Out[35]:

	Hours Playing Video Games	Hours Spent Socializing
0	15.0	1.0
1	0.0	8.0
2	20.0	0.0
3	20.0	20.0

4	0.0	0.0

In [36]:
```
ayu_df = ayu_df.iloc[:, 0:2]

avg_soc = ayu_df[['Hours Playing Video Games', 'Hours Spent Socializing']].mean()
avg_soc
```

Out[36]:
```
Hours Playing Video Games    8.096774
Hours Spent Socializing      7.951613
dtype: float64
```

In [37]:
```
video_games = ayu_df['Hours Playing Video Games']
socializing = ayu_df['Hours Spent Socializing']
video_games.corr(socializing)
```

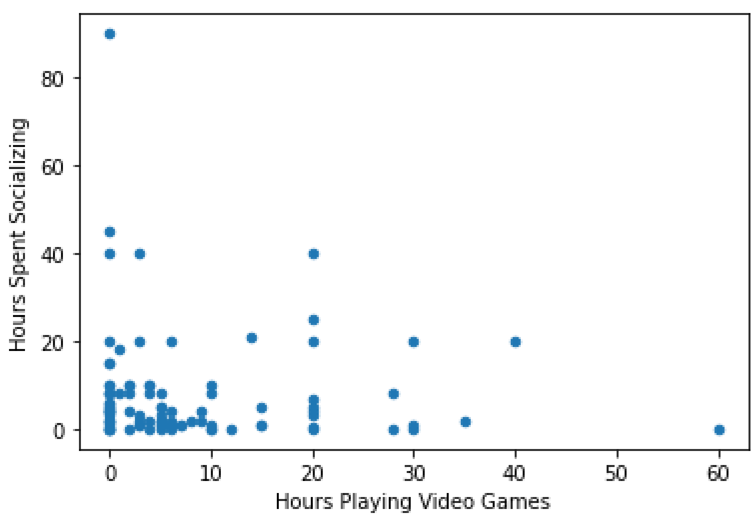
Out[37]:
```
-0.062174490487545592
```

We have a slight negative correlation value, indicating that the two data sets are inversely related, supporting our hypothesis.

In [38]:
```
r = stats.pearsonr(ayu_df['Hours Playing Video Games'], ayu_df['Hours Spent Socializing'
print(r)
```

```
(-0.06217449048754589, 0.5538150740158561)
```

In [39]:
```
ayu_df.plot.scatter(x = 'Hours Playing Video Games', y = 'Hours Spent Socializing');
```



The scatter plot above shows the hours studnets spent playing video games per week vs the hours they spent socializing with friends per week. We notice a slight inverse relationship between the two. As the number of hours spent socializing grew, the hours spent playing video games decreased and vice versa.

In [40]:
```
chi_squared = pd.crosstab(ayu_df['Hours Playing Video Games'], ayu_df['Hours Spent Socia
c, p, dof, expected = chi2_contingency(chi_squared)
p
```

Out[40]:
```
0.6743735095515774
```

Correlation between Time Spent Playing and Watching Video Game Streams per week

Hypothesis: The time spent per week playing video games will correlate with the amount of time spent watching streams of video games being played.

Reasoning: We think that playing video games and watching video games should go in hand. In the instance where the video game is a PvP (Player vs Player) situation, some people like to watch streams of much better players in order to emulate their abilities towards their own style. Watching video games streams also allows the viewer to enjoy the video game without actually playing it and having to make their own decisions.

In [41]:
```
chai_df = pd.read_csv('responses.csv')

chai_df = chai_df.iloc[:, 74:76]
chai_df = chai_df.rename(columns={'74. How many hours do you play video games in an aver
chai_df.iloc[:, 0:2] = chai_df.iloc[:, 0:2].replace(to_replace=r'[^\d.]+', value='', reg
chai_df.iloc[:, 0:2] = chai_df.iloc[:, 0:2].replace(to_replace='', value=0)
chai_df.iloc[:, 0:2] = chai_df.iloc[:, 0:2].replace(np.nan, 0)
chai_df.iloc[:, 2:3] = chai_df.iloc[:, 2:3].fillna('None')

chai_df.head(5)
```

Out[41]:

	HourPlayed	HourWatched
0	15	10
1	0	0
2	20	0
3	20	8
4	0	0

Average Time Spent Playing and Watching Video Game Streams per week

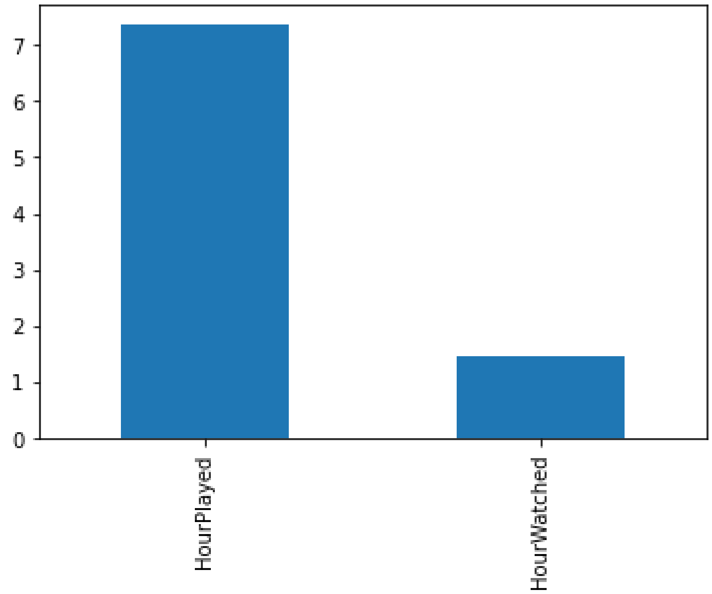
In [42]:
```
chai_df['HourPlayed'] = chai_df['HourPlayed'].astype(float)
chai_df['HourWatched'] = chai_df['HourWatched'].astype(float)

avg_hours = chai_df[['HourPlayed', 'HourWatched']].mean()

avg_hours
```

Out[42]:
```
HourPlayed     7.354545
HourWatched    1.454545
dtype: float64
```

Here, we note that the average time spent playing video games is nearly 4x the time spent watching video game streams.

In [43]:
```
avg_hours.plot.bar()
```

Out[43]:
```
<AxesSubplot:>
```



However, it's important to note that this information considers **all** responses, even those where students put 0 for both `HourWatched` and `HourPlayed` as evident below. Let's look at the average when we drop those values!

Drop our values by seeing if all rows are equal to 0 (We are only looking at `HoursWatched` and `HoursPlayed`). Why exactly are we dropping this? Since we are trying to find the correlation of whether playing video games leads to watching video games, it becomes redudant to have information when a student does **neither** of the things. Without dropping our zero values, there is correlation without stipulation.

In [44]:
```
chai_df = chai_df.loc[~(chai_df==0).all(axis=1)]

chai_df.head(5)
```

Out[44]:

	HourPlayed	HourWatched
0	15.0	10.0
2	20.0	0.0
3	20.0	8.0
7	3.0	0.0
9	5.0	0.0

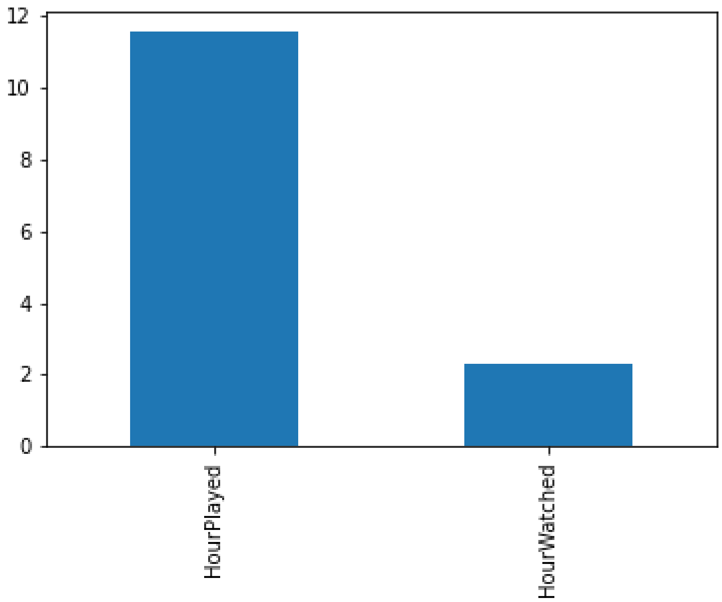
After dropping our zero values, we see that the average hours shifts from 7.35 and 1.45 to 11.56 and 2.29 respectively. Note, that if we wanted to garner a poll of whether students play and watch video games, it would make sense to leave our zero values in. However, we are more interested in students with non-zero responses to either hours spent playing, or hours spent watching.

In [45]:
```
avg_hours = chai_df[['HourPlayed', 'HourWatched']].mean()

avg_hours
```

Out[45]:
```
HourPlayed     11.557143
HourWatched     2.285714
dtype: float64
```

In [46]:
```
avg_hours.plot.bar()
```

Out[46]: <AxesSubplot:>



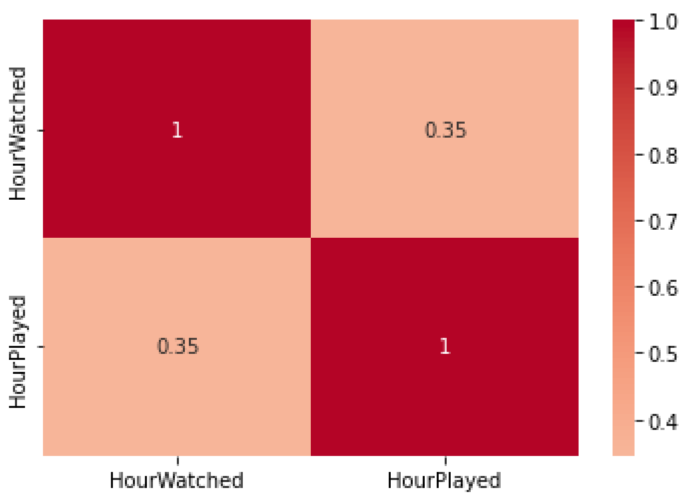
Conducting Correlation Between Hours spent Watching Streams and Hours Spent Playing Games

In [47]:
```
corr1 = chai_df['HourWatched']
corr2 = chai_df['HourPlayed']

print("Correlation Coefficient:",corr2.corr(corr1))
```

```
Correlation Coefficient: 0.34539032240649753
```

In [48]:
```
hours_correlation = df[['HourWatched', 'HourPlayed']].corr()

sns.heatmap(hours_correlation, center=0, cmap="coolwarm", annot=True)
```

Out[48]: <AxesSubplot:>



So, with a correlation coefficient of `0.345`, we can see that there is some positive correlation (albeit low) between Hours spent watching Streams versus Hours spent playing Games. At this point, there is nearly a neglible correlation between the two, but we can save that for until we do our Chi-Squared Test on our Data

Conducting Chi-Squared Test on Data

In our case, we would like to see if there is any significance between `HourWatched` and `HourPlayed`. Before we can proceed into testing, we must first develop our two hypothesis:

- H0: There is **no relationship** between the two variables, and our data is independent
- H1: There **is a relationship** between the two variables, and our data is dependent on the other.

Before we begin, we need to create a smaller subset of data that disregards NaNs and only pays attention to those variables. After that, we calculate the row and column totals for each

In [49]:
```
observed = chai_df.copy()
observed
```

Out[49]:

	HourPlayed	HourWatched
0	15.0	10.0
2	20.0	0.0
3	20.0	8.0
7	3.0	0.0
9	5.0	0.0
...	...	...
104	10.0	0.0
106	5.0	0.0
107	30.0	4.0
108	28.0	2.0
109	20.0	1.0

70 rows × 2 columns

In [50]:
```
hours_count = observed.copy()
hours_count.loc['col_total'] = hours_count.sum(axis=0)
hours_count['row_total'] = hours_count.sum(axis=1)
hours_count
```

Out[50]:

	HourPlayed	HourWatched	row_total
0	15.0	10.0	25.0
2	20.0	0.0	20.0
3	20.0	8.0	28.0
7	3.0	0.0	3.0
9	5.0	0.0	5.0
...	...	...	...
106	5.0	0.0	5.0
107	30.0	4.0	34.0
108	28.0	2.0	30.0
109	20.0	1.0	21.0
col_total	809.0	160.0	969.0

71 rows × 3 columns

In order to create our expected table, we need to multiply the row total to the colum total and divide by the total number of observations for a cell to get our expected count. We can do this utilizing the `np.outer()` function in order to get those totals. Then, we can divide the outputs by the true total, which in this case is `969`.

In [51]:
```
expected = np.outer(hours_count["row_total"][0:70], hours_count.loc["col_total"][0:2]) /

expected = pd.DataFrame(expected)

expected.columns = ['HourPlayed', 'HourWatched']

expected
```

Out[51]:

	HourPlayed	HourWatched
0	20.872033	4.127967
1	16.697626	3.302374
2	23.376677	4.623323
3	2.504644	0.495356
4	4.174407	0.825593
...	...	...
65	8.348813	1.651187
66	4.174407	0.825593
67	28.385965	5.614035
68	25.046440	4.953560
69	17.532508	3.467492

70 rows × 2 columns

Creating Chi-Squared Statistic

After calculating our expected table, we can then calculate the chi-square static value with the below formula.

In [52]:
```
chi_squared_stat = (((observed - expected)**2) / expected).sum().sum()
print("Chi-Squared static value:",chi_squared_stat)
```

```
Chi-Squared static value: 2166.033316451384
```

We can figure out our critical values and p-values. In the case of our experiment, we are utilizing a Confidence Rate of 99.9%. Our table is currently 70 x 2, therefore our degrees of freedom will be 69 (as 69 x 1).

In [53]:
```
critical_value = chi2.ppf(q=0.999, df=69)
print("Critical Value:",critical_value)

p_value = 1 - (chi2.cdf(x=chi_squared_stat, df=69))
print("P Value:", p_value)
```

```
Critical Value: 111.05506556267146
P Value: 0.0
```

Based on the heatmap, we already knew that there is a low positive correlation between the hours spent watching versus the hour spent playing video games. However, a correlation near 30% is subject to potentially being negligible! Since our p-value of 0.00 is less than the required threshold of 0.001, we can reject the null hypothesis and claim that there is some correlation between Hours Spent Watching Video Games and Hours Spent Playing Video Games

Question 4 - What are you Hypothesis?

- The time spent per week streaming videos such as youtube or netflix will correlate with the amount of time per week spent playing video games.
- The further back you sit in a classroom, the more time you spend playing video games.
- The more time a college student spends playing video games, the less time they spend socializing with friends on campus.
- Younger College Students spent hours per week playing video games.
- The time spent per week playing video games will correlate with the amount of time spent watching streams of video games being played.

(Note, that the hypothesis were repeated in their respective sections)

Question 5 - Test your Hypothesis

All questions and hypothesis were tested within their respective sections during question 3, with `name_df` to denote which member worked on each question and came to their own conclusions.

Verify Effectiveness of Chi-Squared and Correlation Tests

A toy data set was utilized and documented in `correlation_calculations.ipynb`. These calculations were done by a member on python, then verified on hand in the supporting `hand_calculations.pdf`.