Gym-Members Dataset Analysis

Disclosure

*This dataset is **artificial**, meaning **some insights may not accurately reflect reality**. Before beginning the analysis, we **must identify the limitations** of what can be meaningfully inferred versus what is clearly a **byproduct of dataset fabrication**.*

*For example, when plotting **Weight vs. Height** for males and females, a clear pattern emerges:*

- ***Females** were assigned **heights between 1.5m and 1.8m** and **weights between 40 kg and 80 kg**.*
- *This artificial constraint means the graph **does not provide real-world insights**, as the data distribution is predefined.*

*Due to such constraints, **certain analyses will be excluded**, as they **do not contribute meaningful conclusions**.*

Summary:

Gym-Members per gender:

	Males	Females
Amount	511	462
Percentage	52.5%	47.5%

Table 1: Amount and percentage of male and female Gym-Members.

Gym-Members per WorkOut Type:

	Strength	Cardio	Yoga	HIIT
Amount	258	255	239	221
Percentage	26.5%	26.2%	24.6%	22.7%

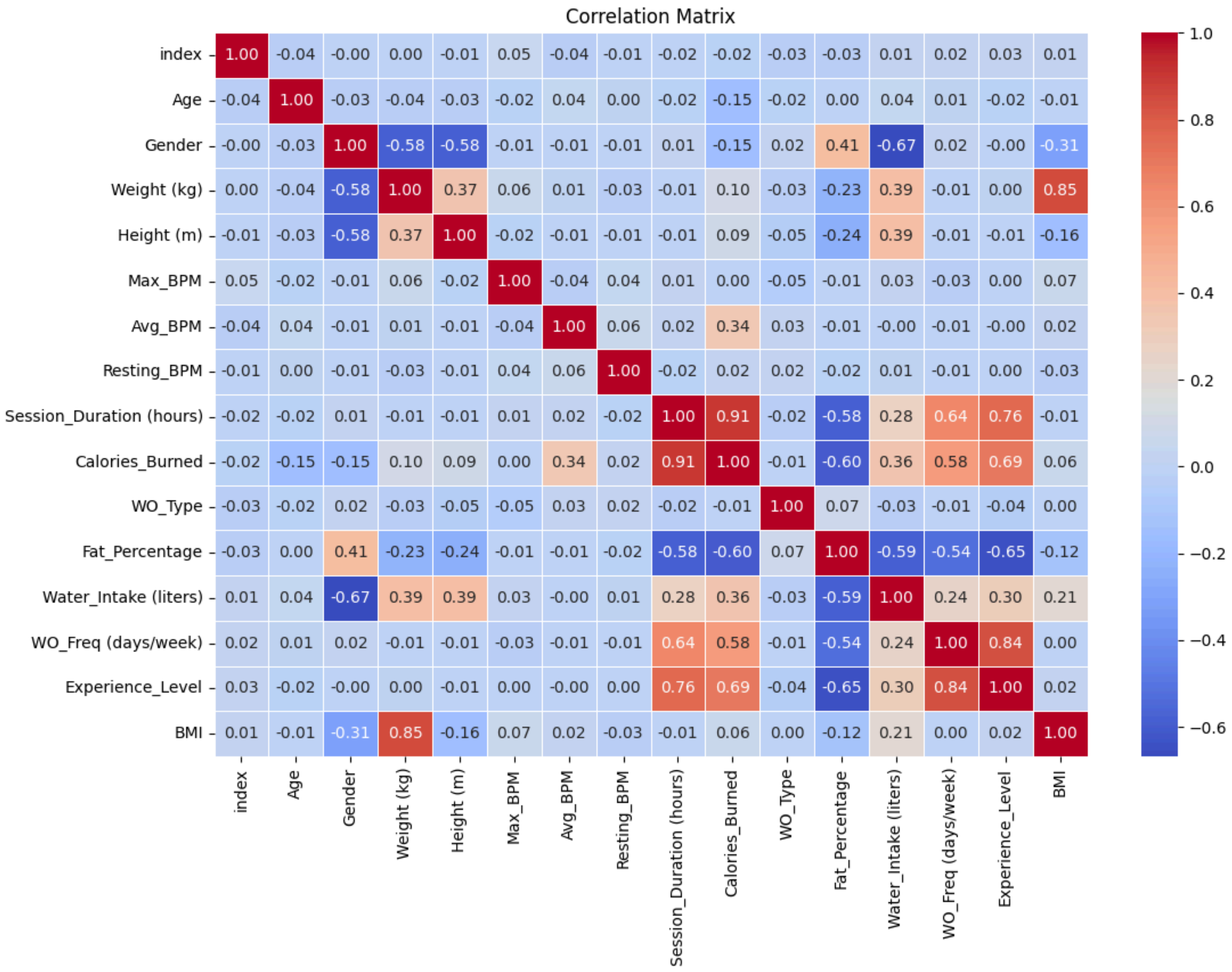
Table 2: Amount and percentage of gym-members that participate in the different WorkOut Types available at the gym.

Attribues general characteristics:

Index	Data Type	#missing	Duplicate	#Unique	Min	Max	Avg	Std dev	Top Value	Freq
Age	int64	0	0	42	18	59	38.7	12.2	N/A	N/A
Gender	object	0	0	2	N/A	N/A	N/A	N/A	Male	511
Weight	float64	0	0	523	40	129.9	73.8	21.2	N/A	N/A
Height	float64	0	0	51	1.5	2	1.7	0.1	N/A	N/A
Max BPM	int64	0	0	40	160	199	179.9	11.5	N/A	N/A
Avg BPM	int64	0	0	50	120	169	143.8	14.3	N/A	N/A
Resting BPM	int64	0	0	25	50	74	62.2	7.3	N/A	N/A
Session Duration	float64	0	0	147	0.5	2	1.2	0.3	N/A	N/A
Calories Burned	float64	0	0	621	303	1783	905.4	272.6	N/A	N/A
WorkOut Type	object	0	0	4	N/A	N/A	N/A	N/A	Strength	258
Fat Percentage	float64	0	0	239	10	35	25	6.2	N/A	N/A
Water Intake	float64	0	0	23	1.5	3.7	2.6	0.6	N/A	N/A
WorkOut Frequency	int64	0	0	4	2	5	3.3	0.9	N/A	N/A
Experience Level	int64	0	0	3	1	3	1.8	0.7	N/A	N/A
BMI	float64	0	0	771	12.3	49.8	24.9	6.7	N/A	N/A

Table 3: General characteristics derived from an exploratory data analysis (EDA) of the database.

<u>Correlation Matrix:</u>



	index	Age	Gender	Weight (kg)	Height (m)	Max_BPM	Avg_BPM	Resting_BPM	Session_Duration (hours)	Calories_Burned	WO_Type	Fat_Percentage	Water_Intake (liters)	WO_Freq (days/week)	Experience_Level	BMI
index	1.00	-0.04	-0.00	0.00	-0.01	0.05	-0.04	-0.01	-0.02	-0.02	-0.03	-0.03	0.01	0.02	0.03	0.01
Age	-0.04	1.00	-0.03	-0.04	-0.03	-0.02	0.04	0.00	-0.02	-0.15	-0.02	0.00	0.04	0.01	-0.02	-0.01
Gender	-0.00	-0.03	1.00	-0.58	-0.58	-0.01	-0.01	-0.01	0.01	-0.15	0.02	0.41	-0.67	0.02	-0.00	-0.31
Weight (kg)	0.00	-0.04	-0.58	1.00	0.37	0.06	0.01	-0.03	-0.01	0.10	-0.03	-0.23	0.39	-0.01	0.00	0.85
Height (m)	-0.01	-0.03	-0.58	0.37	1.00	-0.02	-0.01	-0.01	-0.01	0.09	-0.05	-0.24	0.39	-0.01	-0.01	-0.16
Max_BPM	0.05	-0.02	-0.01	0.06	-0.02	1.00	-0.04	0.04	0.01	0.00	-0.05	-0.01	0.03	-0.03	0.00	0.07
Avg_BPM	-0.04	0.04	-0.01	0.01	-0.01	-0.04	1.00	0.06	0.02	0.34	0.03	-0.01	-0.00	-0.01	-0.00	0.02
Resting_BPM	-0.01	0.00	-0.01	-0.03	-0.01	0.04	0.06	1.00	-0.02	0.02	0.02	-0.02	0.01	-0.01	0.00	-0.03
Session_Duration (hours)	-0.02	-0.02	0.01	-0.01	-0.01	0.01	0.02	-0.02	1.00	0.91	-0.02	-0.58	0.28	0.64	0.76	-0.01
Calories_Burned	-0.02	-0.15	-0.15	0.10	0.09	0.00	0.34	0.02	0.91	1.00	-0.01	-0.60	0.36	0.58	0.69	0.06
WO_Type	-0.03	-0.02	0.02	-0.03	-0.05	-0.05	0.03	0.02	-0.02	-0.01	1.00	0.07	-0.03	-0.01	-0.04	0.00
Fat_Percentage	-0.03	0.00	0.41	-0.23	-0.24	-0.01	-0.01	-0.02	-0.58	-0.60	0.07	1.00	-0.59	-0.54	-0.65	-0.12
Water_Intake (liters)	0.01	0.04	-0.67	0.39	0.39	0.03	-0.00	0.01	0.28	0.36	-0.03	-0.59	1.00	0.24	0.30	0.21
WO_Freq (days/week)	0.02	0.01	0.02	-0.01	-0.01	-0.03	-0.01	-0.01	0.64	0.58	-0.01	-0.54	0.24	1.00	0.84	0.00
Experience_Level	0.03	-0.02	-0.00	0.00	-0.01	0.00	-0.00	0.00	0.76	0.69	-0.04	-0.65	0.30	0.84	1.00	0.02
BMI	0.01	-0.01	-0.31	0.85	-0.16	0.07	0.02	-0.03	-0.01	0.06	0.00	-0.12	0.21	0.00	0.02	1.00

Figure 1: Correlation matrix of all the attributes of the database.

By analyzing **correlation_Matrix.png**, we can observe various relationships between attributes. A correlation above **|0.2|** is considered meaningful:

- **Positive correlation (≥ 0.2):** If one attribute increases, the other tends to increase.
- **Negative correlation (≤ -0.2):** If one attribute increases, the other tends to decrease.
- **Weak or no correlation (-0.2 to 0.2):** The attributes are largely independent.

General characteristics:

- **Age**, as expected, seems to have <u>no distinguishable correlation</u> with any other variable.
- For **gender** I established that Male is -1 and Female is 1 so it can be used in the correlation matrix. A high positive correlation with gender indicates a stronger

association with being Female, while a strong negative correlation suggests a stronger association with being Male.

  - **Female correlations**: Fat Percentage shows a positive correlation of 0.41, meaning higher fat percentage is associated with being Female.
  - **Male correlations**: Weight (-0.58), Height (-0.58), Water Intake (-0.67), and BMI (-0.31) show negative correlations, meaning higher values for these features are associated with being Male.

Body:

- **Weight** seems to be correlated to being Male (-0.58), positively correlated to Height (0.37), negatively correlated to Fat Percentage (-0.23), positively correlated to Water Intake (0.39), and highly correlated to BMI (0.85).
- **Height** seems to be correlated to being Male (-0.58), positively correlated to Weight (0.37), negatively correlated to Fat Percentage (-0.24), positively correlated to Water Intake (0.39), and highly correlated to BMI (0.85).
- **Fat Percentage** seems to be correlated to being Female (0.41), negatively correlated to Weight (-0.23), negatively correlated to Height (-0.24), negatively correlated to Session Duration (-0.58), negatively correlated to Calories Burned (-0.60), negatively correlated to Water Intake (-0.59), negatively correlated to WorkOut Frequency (-0.54), and negatively correlated to Experience Level (-0.65).
- **BMI** seems to be correlated to being Male (-0.31), positively correlated to Weight (0.85), and positively correlated to Water Intake (0.21).

Heart Rate:

- **Max BPM** seems to have no distinguishable correlation with any other variable.
- **Average BPM** seems to only be positively correlated to Calories Burned (0.34).
- **Resting BPM** seems to have no distinguishable correlation with any other variable.

Workout related attributes:

- **Session Duration** seems to be highly correlated to Calories Burned (0.91) (as expected), negatively correlated to Fat Percentage (-0.58), positively correlated to Water Intake (0.28), positively correlated to WorkOut Frequency (0.64), and highly correlated to Experience Level (0.76).
- **Calories Burned** seems to be positively correlated to Average BPM (0.34), highly correlated to Session Duration (0.91), negatively correlated to Fat Percentage (-0.60), positively correlated to Water Intake (0.36), positively correlated to WorkOut Frequency (0.58), and positively correlated to Experience level (0.69).
- **WorkOut Type** seems to have no distinguishable correlation with any other variable.
- **Water Intake** seems to be correlated to being Male (-0.67), positively correlated to Weight (0.39), positively correlated to Height (0.39), positively correlated to Session Duration (0.28), positively correlated to Calories Burned (0.36), negatively correlated to Fat Percentage (-0.59), positively correlated to WorkOut Frequency (0.24), positively correlated to Experience Level (0.30), and positively correlated to BMI (0.21).
- **WorkOut Frequency** seems to be positively correlated to Session Duration (0.64), positively correlated to Calories Burned (0.58), negatively correlated to Fat

Percentage (-0.54), positively correlated to Water Intake (0.24), and highly correlated to Experience Level (0.84).

- **Experience Level** seems to be positively correlated to Session Duration (0.76), positively correlated to Calories Burned (0.69), negatively correlated to Fat Percentage (-0.65), positively correlated to Water Intake (0.30), and highly correlated to WorkOut Frequency (0.84).

Bar Graphs:

Divided by gender:

Age Groups: The distribution of males and females across age groups appears similar.

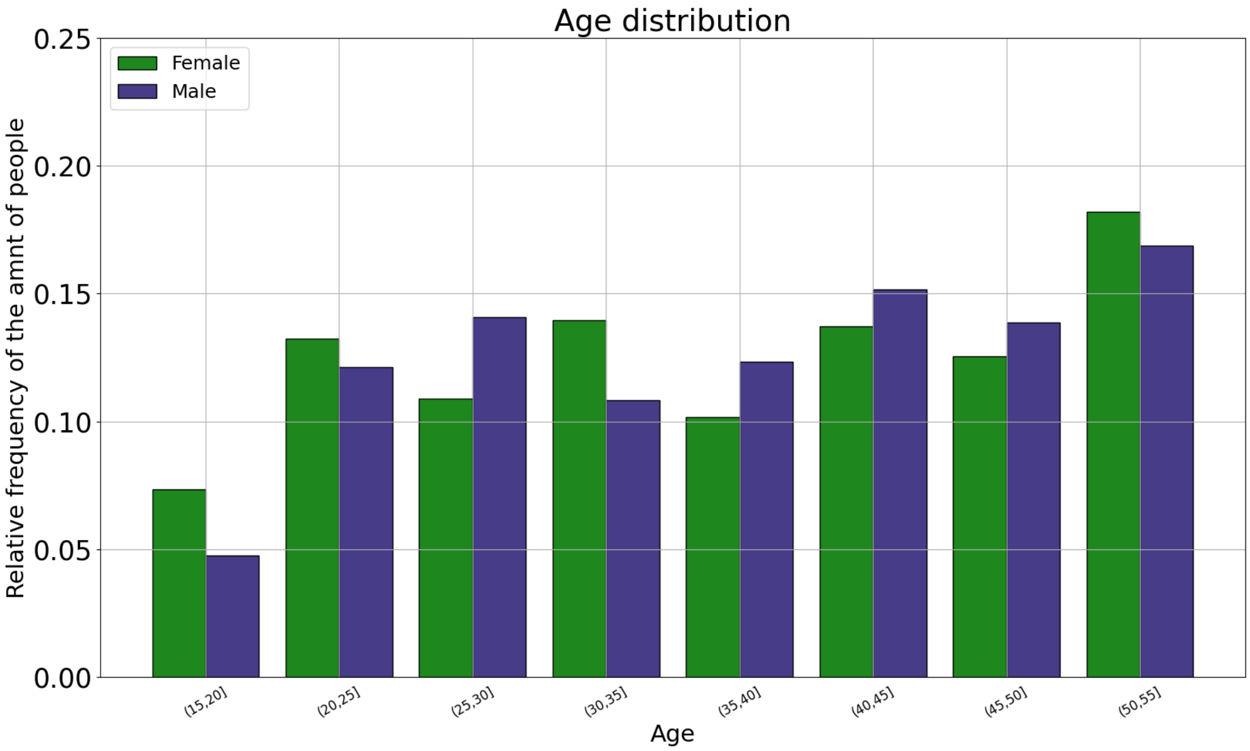


Figure 2: Age distribution of males and females.

Height & Weight:

- Females tend to be **shorter** than males. Females average around 1.62 m and males around 1.77 m.

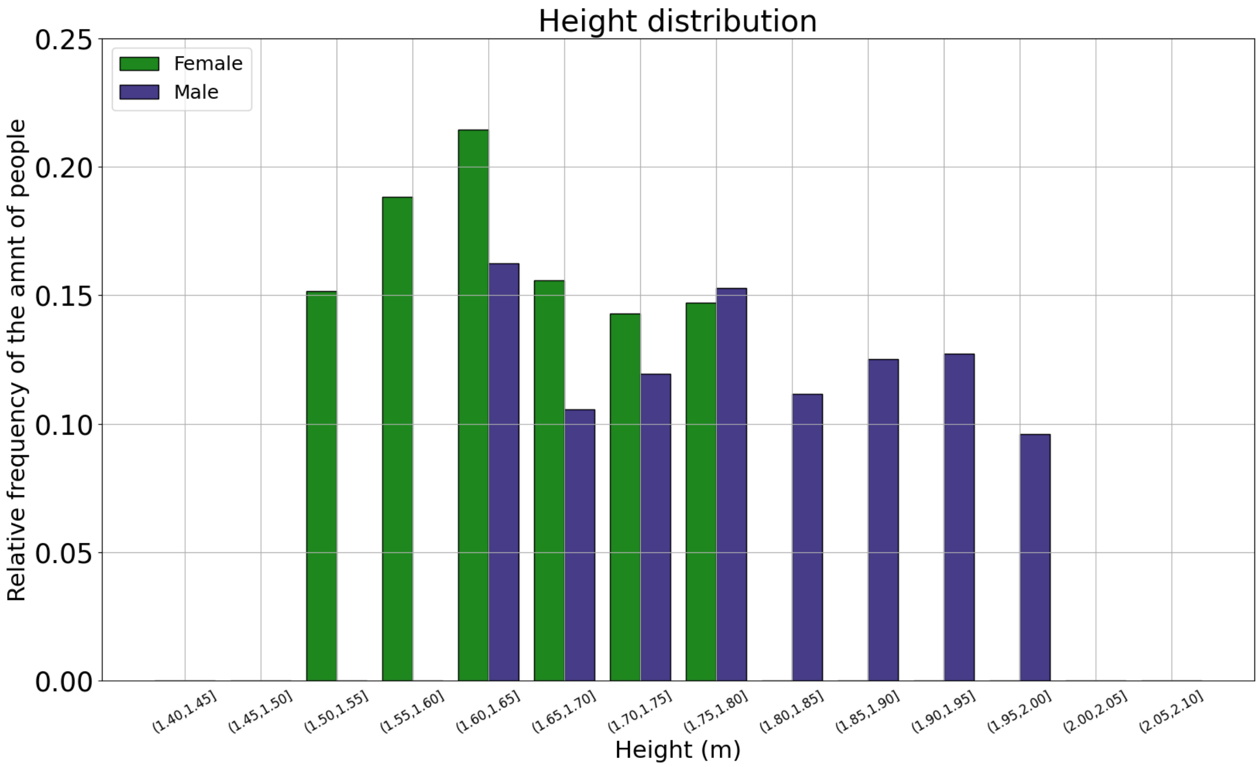


Figure 3: Height (m) distribution of males and females.

- Males generally weigh **more**, with a **high dispersion** and a **peak around 80-90 kg**. Females' **peak** is **around 60 kg**.

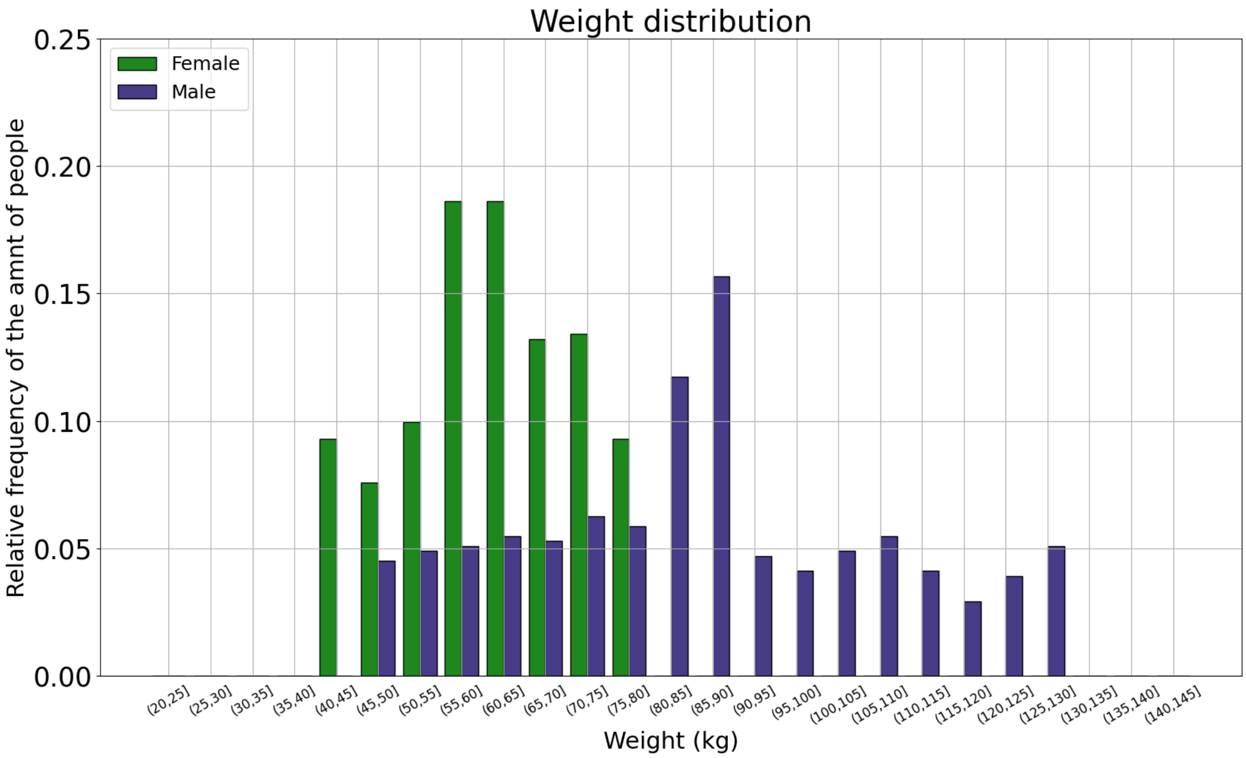


Figure 4: Weight (kg) distribution of males and females.

Heart Rate: Both **Max BPM** and **Resting BPM** are similar for males and females.

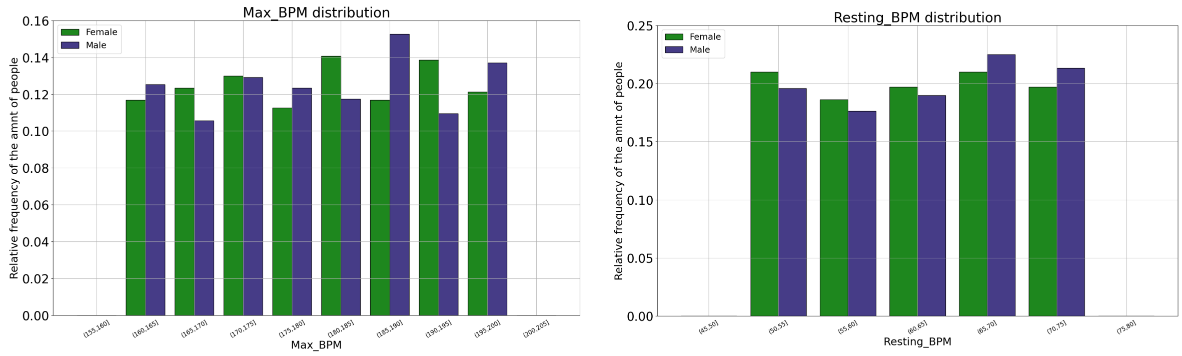


Figure 5: Max BPM and Resting BPM distribution of males and females.

Session Duration:

- Three distinct session durations are observed for both genders:
  - **30 min to 1 hour**
  - **1 hour to 1:30 hours** (most popular, with 61% of the gym members)
  - **1:30 hours to 2 hours**

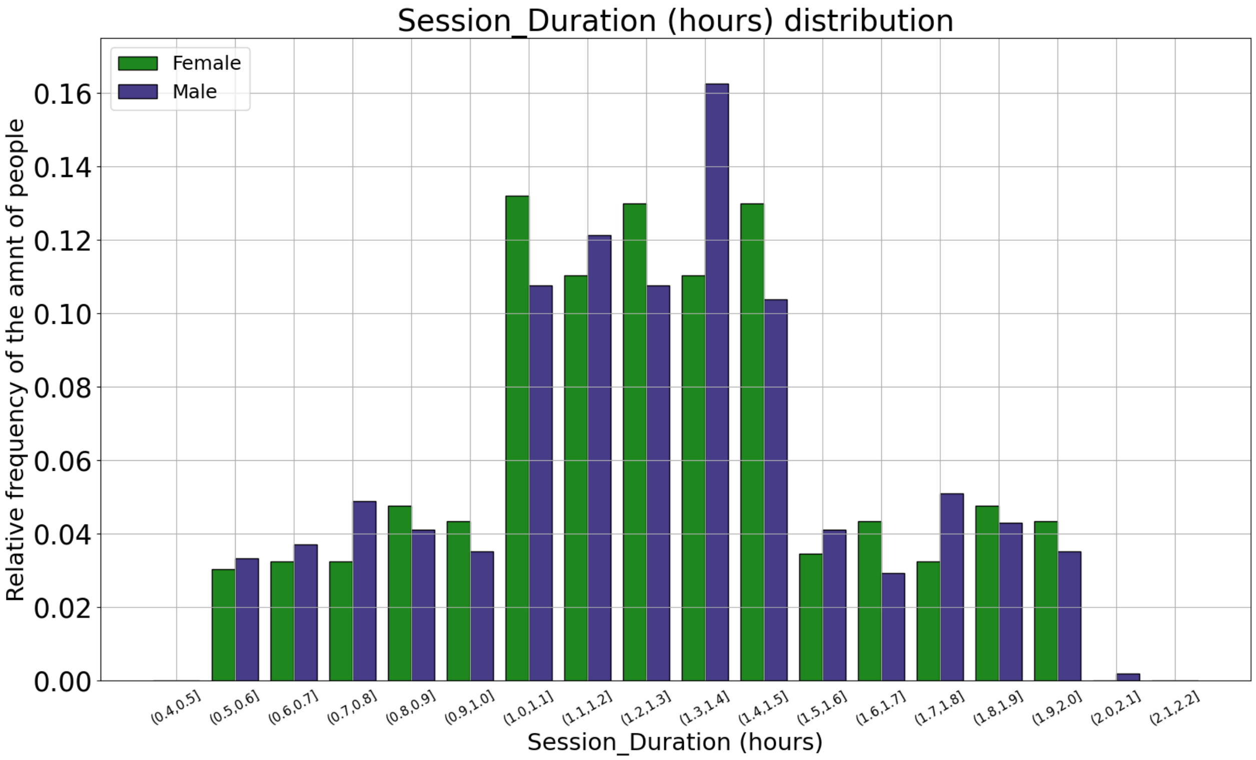


Figure 6: Session duration (hours) distribution of males and females.

Fat Percentage:

- Females tend to have a **higher fat percentage** than males.
- Both genders show **two distinct fat percentage groups**:
    - **Males:** 19.7% fall between **10-16%**, while the rest range from **20-32%**.
    - **Females:** 19.2% fall between **14-20%**, while the rest range from **24-36%**.

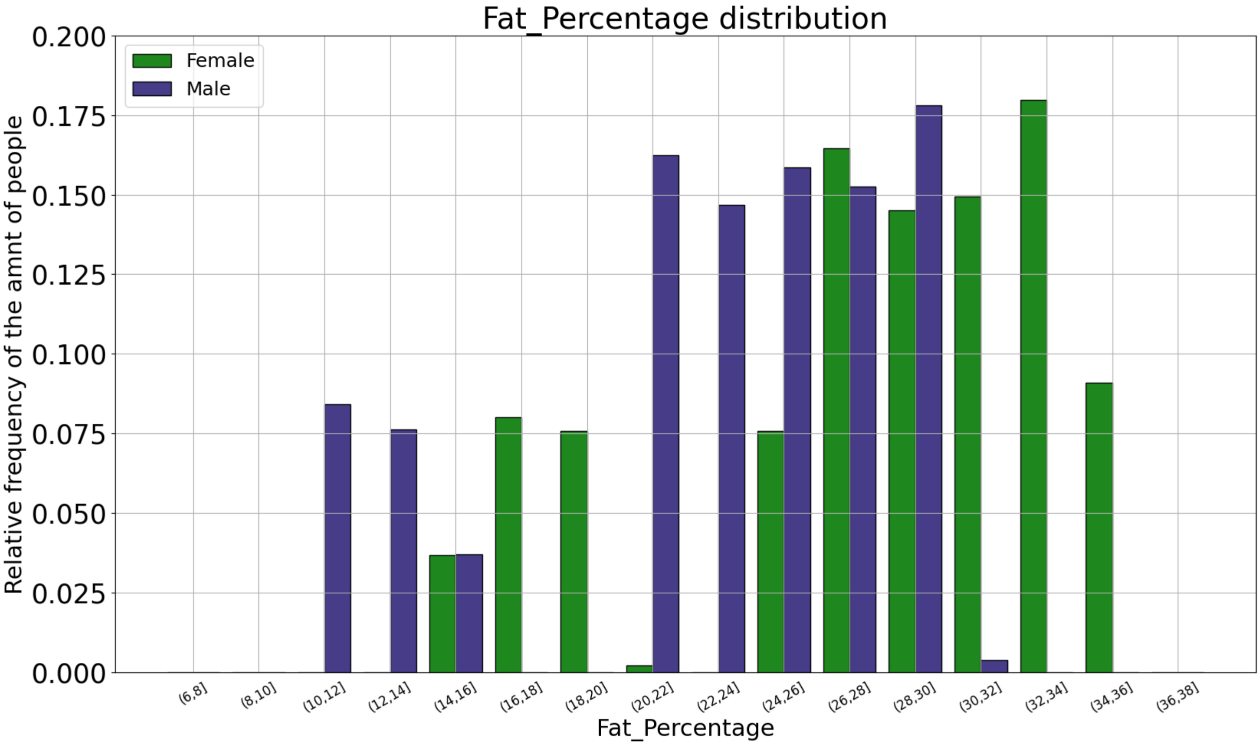


Figure 7: Fat percentage distribution of males and females.

Water Intake:

- Males tend to drink more water than females.
- High percentages are observed in specific ranges:
    - **27% of females** drink **2.6 to 2.8 L**.
    - **32% of males** drink **3.4 to 3.6 L**.

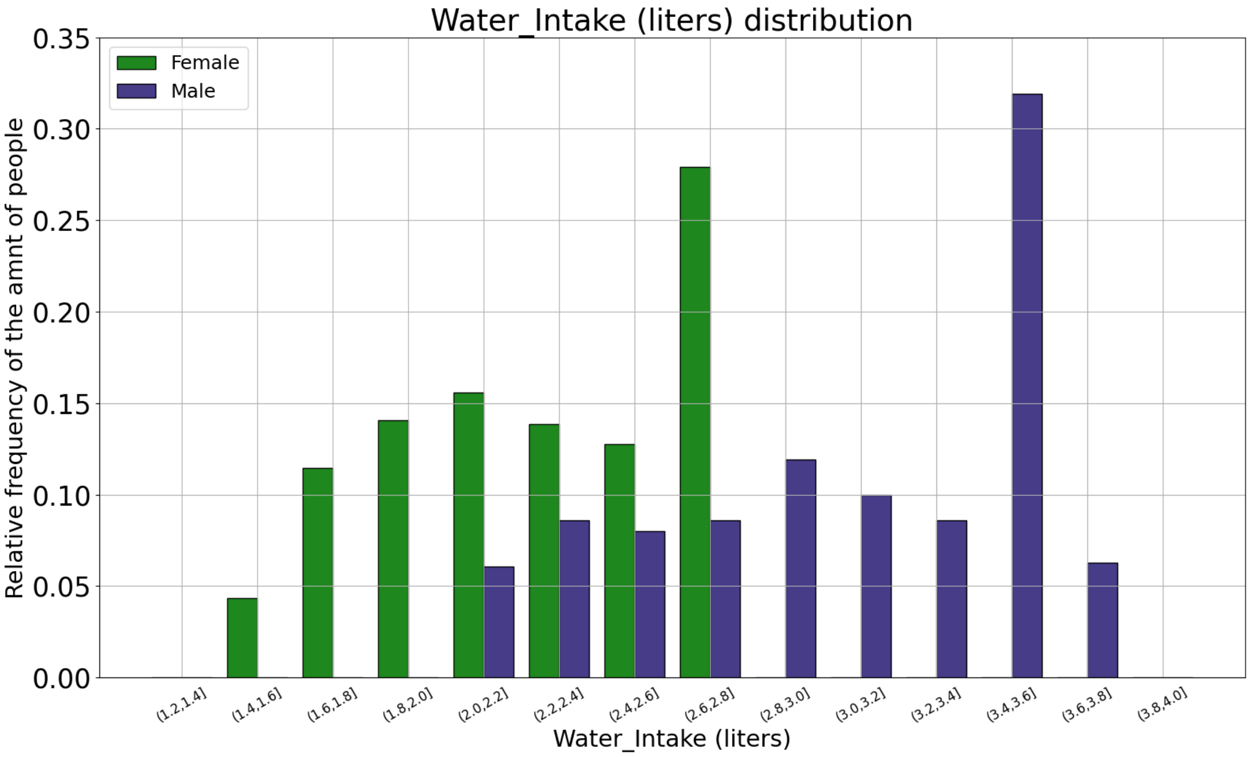


Figure 8: Water intake (L) distribution of males and females.

Workout Frequency & Experience Level: Similar distributions for both genders.

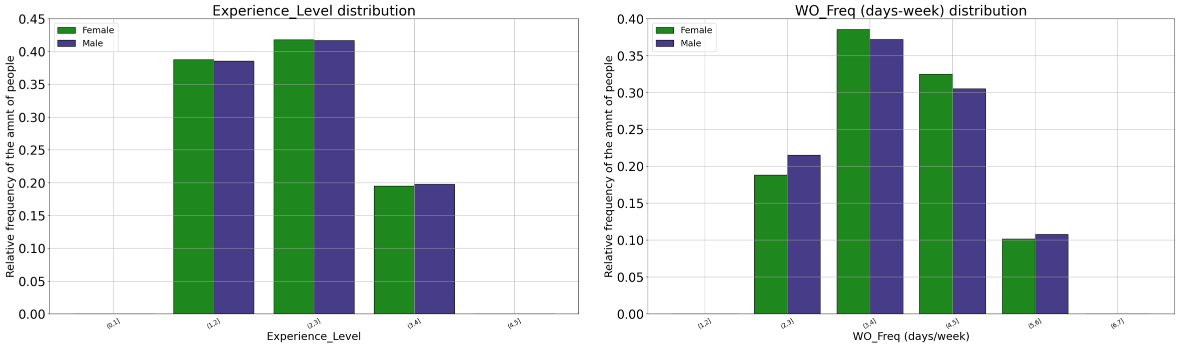


Figure 9: Workout frequency and experience level distribution of males and females.

BMI Distribution:

- Females: **~20 ± 10** (more centered distribution).
- Males: **~25 ± 20** (more dispersed).
- Both follow a **Gaussian distribution**.

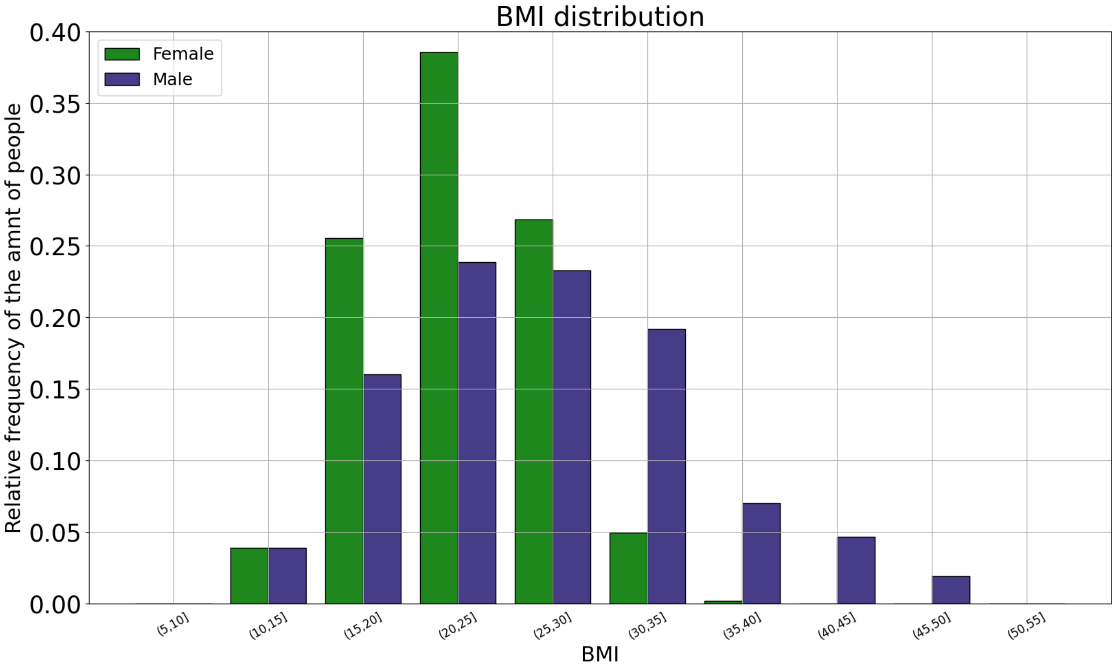


Figure 10: BMI distribution of males and females.

Divided by WorkOut Type:

Age Distribution:

- **Yoga:** 52% of attendees are **between 35-50**.
- **HIIT:** 36% are either **20-25 or 50-55**.
- **Cardio:** 7% are **15-20** years old, while the rest are **evenly distributed between 20-55**.
- **Strength Training:** Participation increases with **age**.

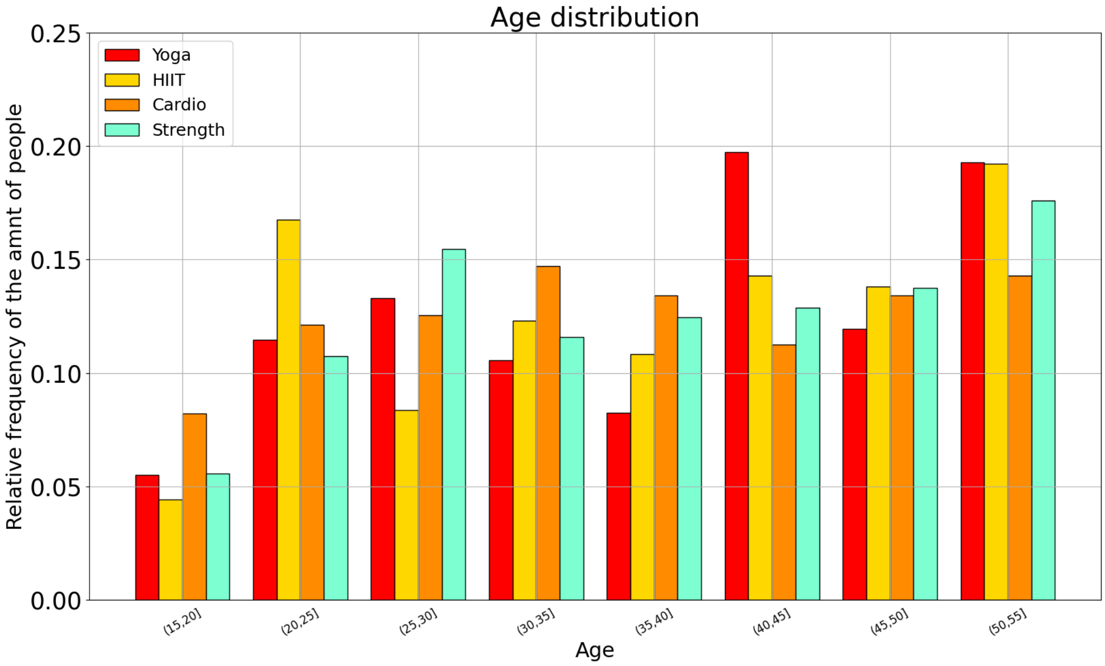


Figure 11: Age distribution of workout types.

Other Factors (Calories Burned, Resting BPM, Session Duration, Water Intake, and Max BPM): These metrics appear **independent of the workout type**.

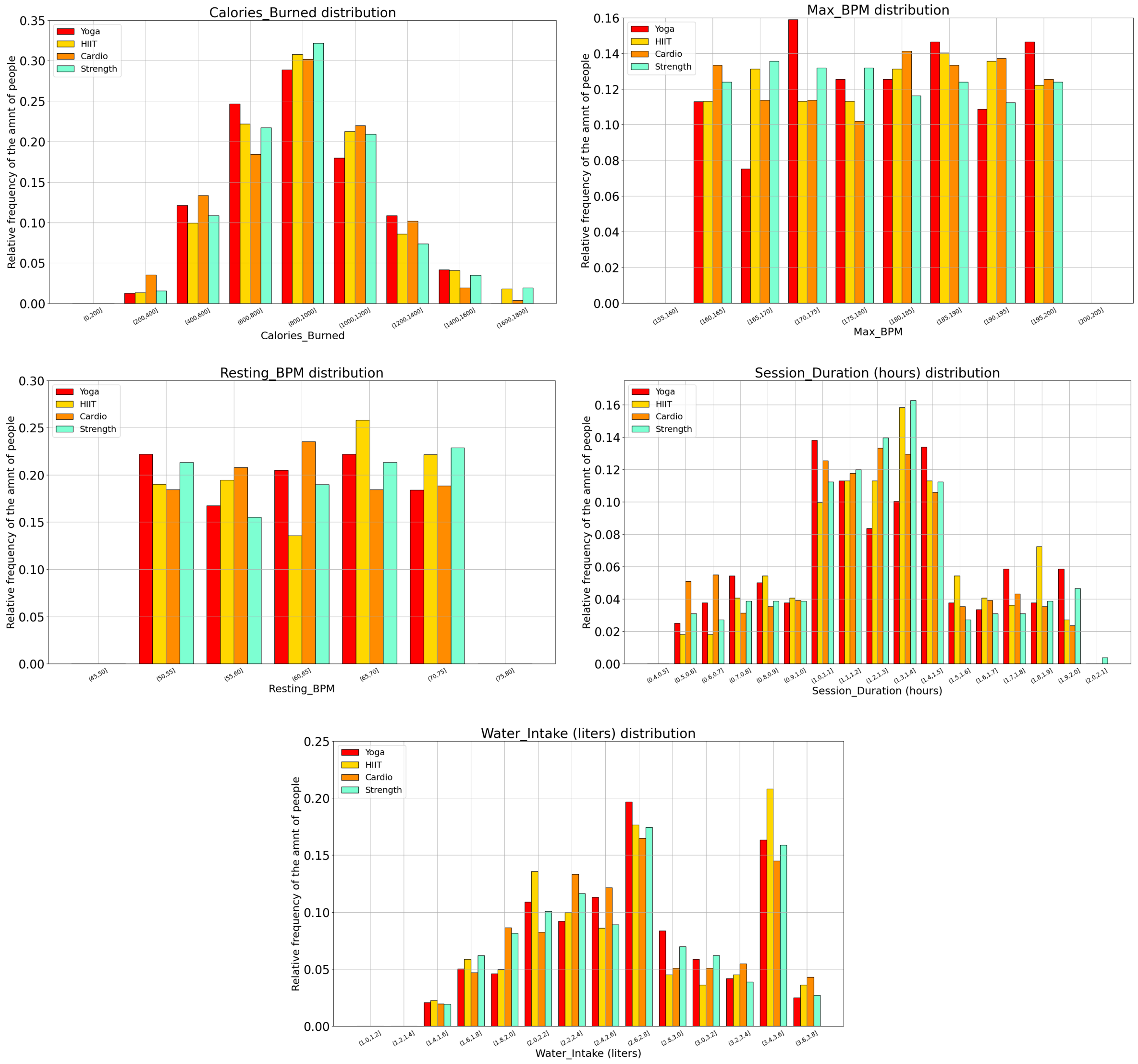


Figure 12: Calories burned, max BPM, resting BPM, session duration and water intake distribution of workout types.

Joint Plot Analysis

- **Session Duration & Calories Burned:**
  - A **strong positive correlation** is observed: **longer sessions lead to higher calorie burn**, as expected.
  - This trend is **consistent across both males and females**.

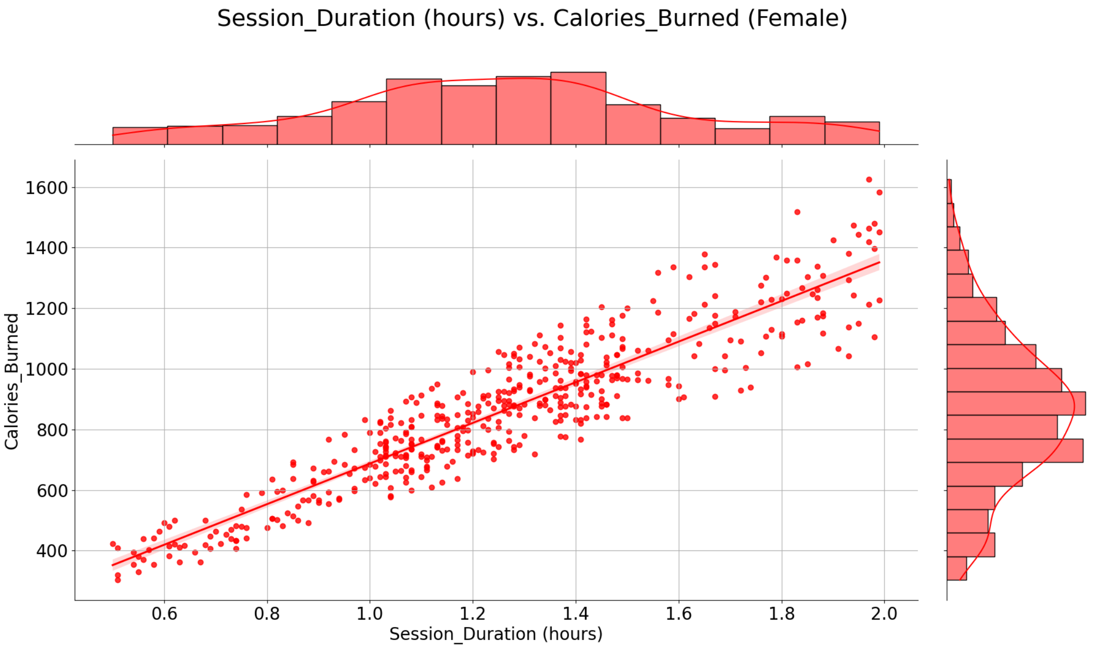


Figure 13: Joint plot comparing session duration and calories burned, for females.

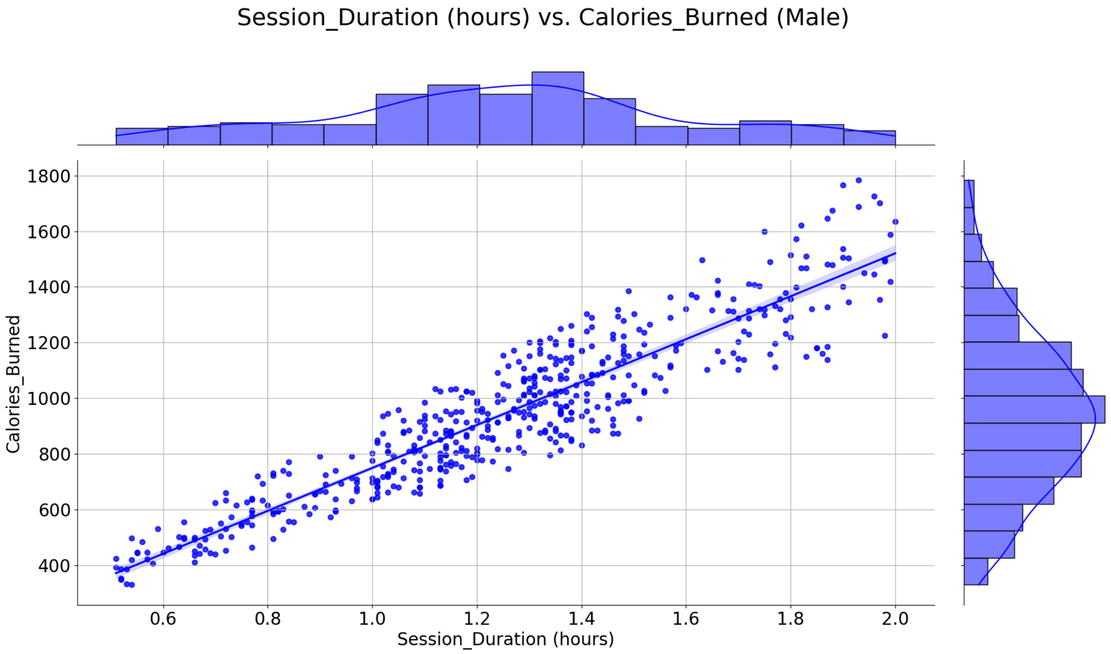


Figure 14: Joint plot comparing session duration and calories burned, for males.

- **Weight & BMI:**
  - As expected, **weight is positively correlated with BMI — heavier individuals** tend to have **higher BMI values**.
  - This holds true **regardless of gender**.

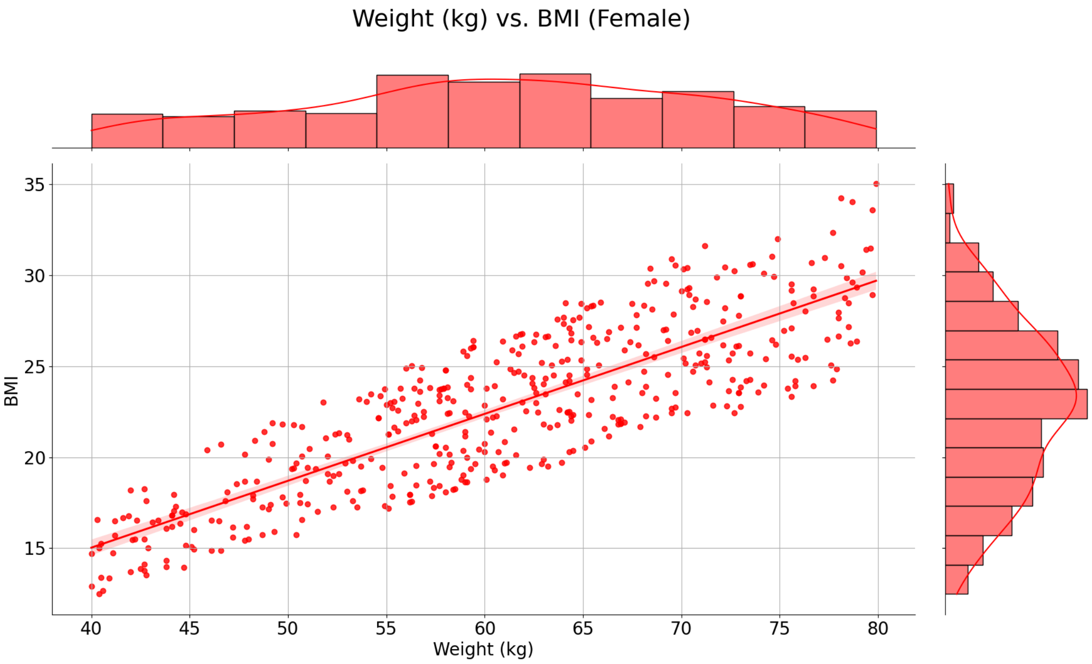


Figure 15: Joint plot comparing weight (kg) and BMI, for females.

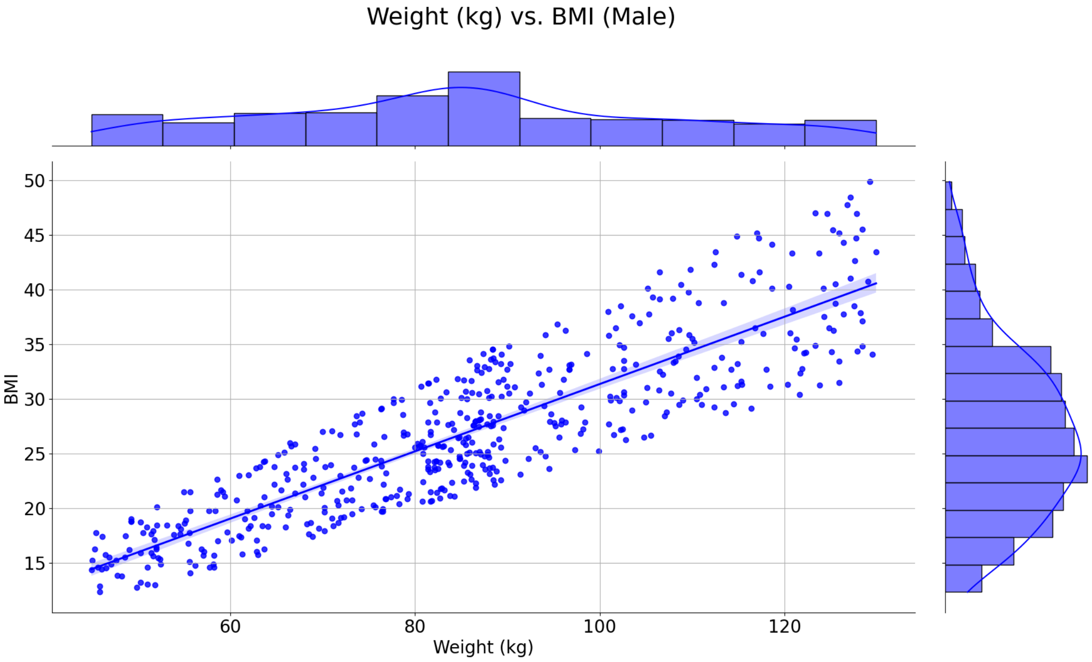


Figure 16: Joint plot comparing weight (kg) and BMI, for males.

- **Weight & Resting BPM:**
  - **No significant correlation** is found between weight and resting BPM.
  - This suggests that **individuals with different weights can have similar resting heart rates**.

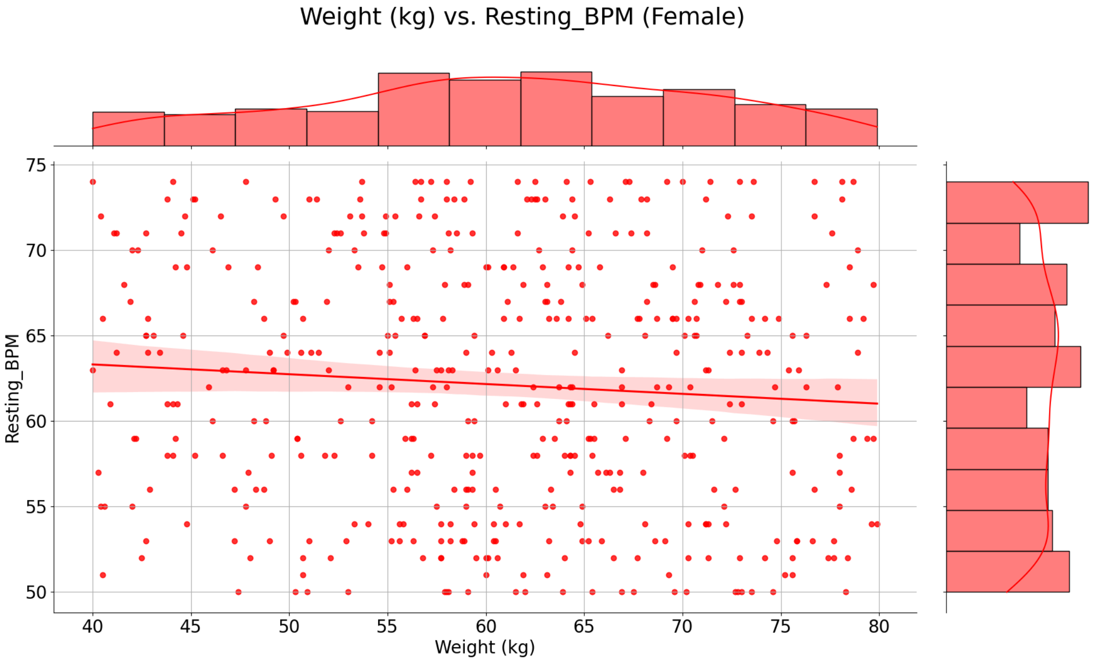


Figure 17: Joint plot comparing weight (kg) and Resting BPM, for females.

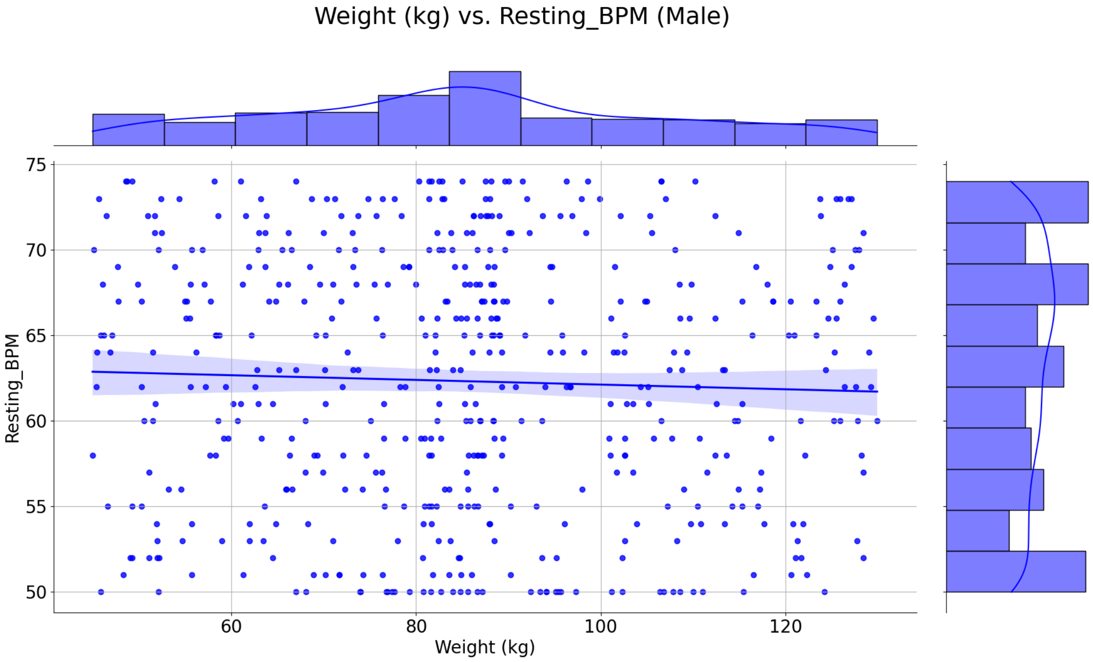


Figure 18: Joint plot comparing weight (kg) and Resting BPM, for males.

TensorFlow:

I wanted to make a model that could predict the amount of calories a new gym member would burn, depending on numerical features, such as: Age, Weight, Height, Session Duration, etc. and categorical features: Gender and WorkOut Type.

In order to train the model, I splitted the database:

- **80%** of it was used to **train** the **model**. **80%** of that was used to actually **train** the model and **20%** was used to **validate** it.
- **20%** was **held** till the end to evaluate the model using data not used for training.

I **scaled** all of the **numerical values** using the following formula:

$$X_{scaled} = \frac{X - \mu}{\sigma}$$

where μ and σ is the mean and the std of the attribute, respectively. I also **took out** a few **outliers** to **improve** the **fitting** of the model and **transformed** the **categorical columns** into numbers so they can also be **used** in the **training** of the model.

I built a **neural network** using **TensorFlow** with the following architecture:

- **Three hidden layers** with **ReLU activation**, each having 10, 30, and 64 neurons, respectively.
- A **Dropout layer (0.2)** to prevent overfitting.
- A **linear activation output layer** since this is a regression problem.
- The model was compiled with **Mean Squared Error (MSE)** as the loss function and **Adam optimizer** for efficient training.
- **Up to 200 epochs** to allow sufficient learning.
- **Batch size of 32**, meaning weights are updated after processing 32 samples at a time.
- An **early stopping mechanism** was applied to halt training when the validation loss stopped improving, preventing overfitting.

After training, I evaluated the model using **Relative Root Mean Squared Error (Rel RMSE), and R-squared (R²).**

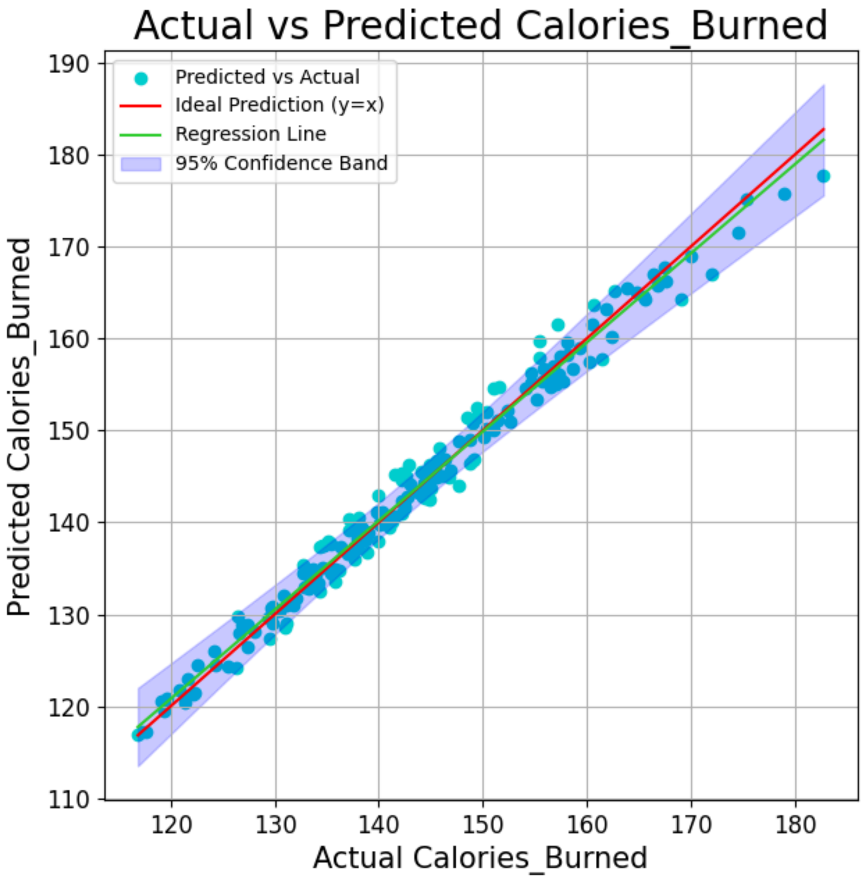


Figure 19: Graph comparing predicted calories burned vs. actual calories burned.

The model achieved an **R² of 0.982**, indicating that it captures a significant portion of the variance in calorie expenditure. Additionally, it has a **relative RMSE of 0.012**, meaning that the model's error is about 1.2% of the average calories burned, which suggests a reasonably accurate prediction performance. This makes it a useful tool for estimating caloric burn for new gym members based on their physical attributes and workout details.