

As a Fitness Coach/Certified Personal Trainer, I'm aware of the perceived misconceptions of how effective bodyweight exercises are when it comes to managing healthy weight and resting heart rate (pulse). This experiment attempts to highlight the effects of an infamous but efficient movement I call "KMBAs"(for personal reasons), and the physiological impacts when performed at different times of the day and the duration of time. The initial cell execution count reflects the addition of the r2_score library after the linear regression plot.

```
In [15]: import pandas as pd
import numpy as np
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import r2_score
```

9 sets of 10 Burpees(KMBAs) performed at different times of the day, for 31 consecutive days, monitoring blood pressure before and after the exercise, pulse rate, and duration for performing this calisthenic movement reputed to be one of the most efficient for maintaining fitness goals, with no equipment.

```
In [3]: kinesthetics = "90_KMBAs"
Kinesthetics = pd.read_csv("90_KMBAs.csv", encoding = 'unicode_escape')
```

A snapshot of the first 5 rows of the dataframe, revealing missing values.

```
In [4]: Kinesthetics.head()
```

Out[4]:

	Day	Pre 90 KMBAs Systolic	Pre 90 KMBAs Diastolic	Pre 90 KMBAs Pulse	Post 90 KMBAs Systolic	Post 90 KMBAs Diastolic	Post 90 KMBAs Pulse	Clock Time	Hour of Day
0	1	133	83	53	141	84	68	NaN	AM
1	2	132	79	51	130	84	75	NaN	AM
2	3	135	73	51	144	86	70	NaN	AM
3	4	128	78	57	130	80	65	18:00	AM
4	5	136	78	50	131	85	69	14:59	PM

An overview of the entire dataset, showing areas that need cleaning/preprocessing.

```
In [5]: Kinesthetics.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 31 entries, 0 to 30
Data columns (total 9 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Day                                    31 non-null    int64
1   Pre 90 KMBAs Systolic                 31 non-null    int64
2   Pre 90 KMBAs Diastolic                 31 non-null    int64
3   Pre 90 KMBAs Pulse                     31 non-null    int64
4   Post 90 KMBAs Systolic                 31 non-null    int64
5   Post 90 KMBAs Diastolic                 31 non-null    int64
6   Post 90 KMBAs Pulse                     31 non-null    int64
7   Clock Time                             27 non-null    object
8   Hour of Day                             31 non-null    object
dtypes: int64(7), object(2)
memory usage: 2.3+ KB
```

Handling missing values to facilitate statistical analysis.

```
In [6]: # Imputation of mean value for NaNs in "Clock Time" column
imputer = SimpleImputer(strategy = 'mean')
Kinesthetics['Clock Time'] = Kinesthetics['Clock Time'].fillna(Kinesthetics[

print(Kinesthetics.head())
```

	Day	Pre 90 KMBAs Systolic	Pre 90 KMBAs Diastolic	Pre 90 KMBAs Pulse	\
0	1	133	83	53	
1	2	132	79	51	
2	3	135	73	51	
3	4	128	78	57	
4	5	136	78	50	

	Post 90 KMBAs Systolic	Post 90 KMBAs Diastolic	Post 90 KMBAs Pulse	\
0	141	84	68	
1	130	84	75	
2	144	86	70	
3	130	80	65	
4	131	85	69	

	Clock Time	Hour of Day
0	13:08	AM
1	13:08	AM
2	13:08	AM
3	18:00	AM
4	14:59	PM

Modifying the AM/PM values to numeric (1s and 0s).

```
In [7]: # Binarization of "Hour of Day" column from AM/PM to 1/0
Kinesthetics['Hour of Day'] = Kinesthetics['Hour of Day'].apply(lambda x: 1

# Print the updated dataset
print(Kinesthetics.head())
```

	Day	Pre 90 KMBAs Systolic	Pre 90 KMBAs Diastolic	Pre 90 KMBAs Pulse	\
0	1	133	83	53	
1	2	132	79	51	
2	3	135	73	51	
3	4	128	78	57	
4	5	136	78	50	

	Post 90 KMBAs Systolic	Post 90 KMBAs Diastolic	Post 90 KMBAs Pulse	\
0	141	84	68	
1	130	84	75	
2	144	86	70	
3	130	80	65	
4	131	85	69	

	Clock Time	Hour of Day
0	13:08	1
1	13:08	1
2	13:08	1
3	18:00	1
4	14:59	0

Modifying the minutes and seconds format, to seconds, in order for the Clock Time values to become integers for analysis.

```
In [8]: # Conversion of "Clock Time" column values to seconds
Kinesthetics['Clock Time'] = Kinesthetics['Clock Time'].apply(lambda x: int(
print(Kinesthetics.head())
```

	Day	Pre 90 KMBAs Systolic	Pre 90 KMBAs Diastolic	Pre 90 KMBAs Pulse	\
0	1	133	83	53	
1	2	132	79	51	
2	3	135	73	51	
3	4	128	78	57	
4	5	136	78	50	

	Post 90 KMBAs Systolic	Post 90 KMBAs Diastolic	Post 90 KMBAs Pulse	\
0	141	84	68	
1	130	84	75	
2	144	86	70	
3	130	80	65	
4	131	85	69	

	Clock Time	Hour of Day
0	788	1
1	788	1
2	788	1
3	1080	1
4	899	0

Dataset is processed and ready for statistical analysis.

```
In [9]: # Summary Statistics
summary_stats = Kinesthetics.describe()
```

```
print(summary_stats)
```

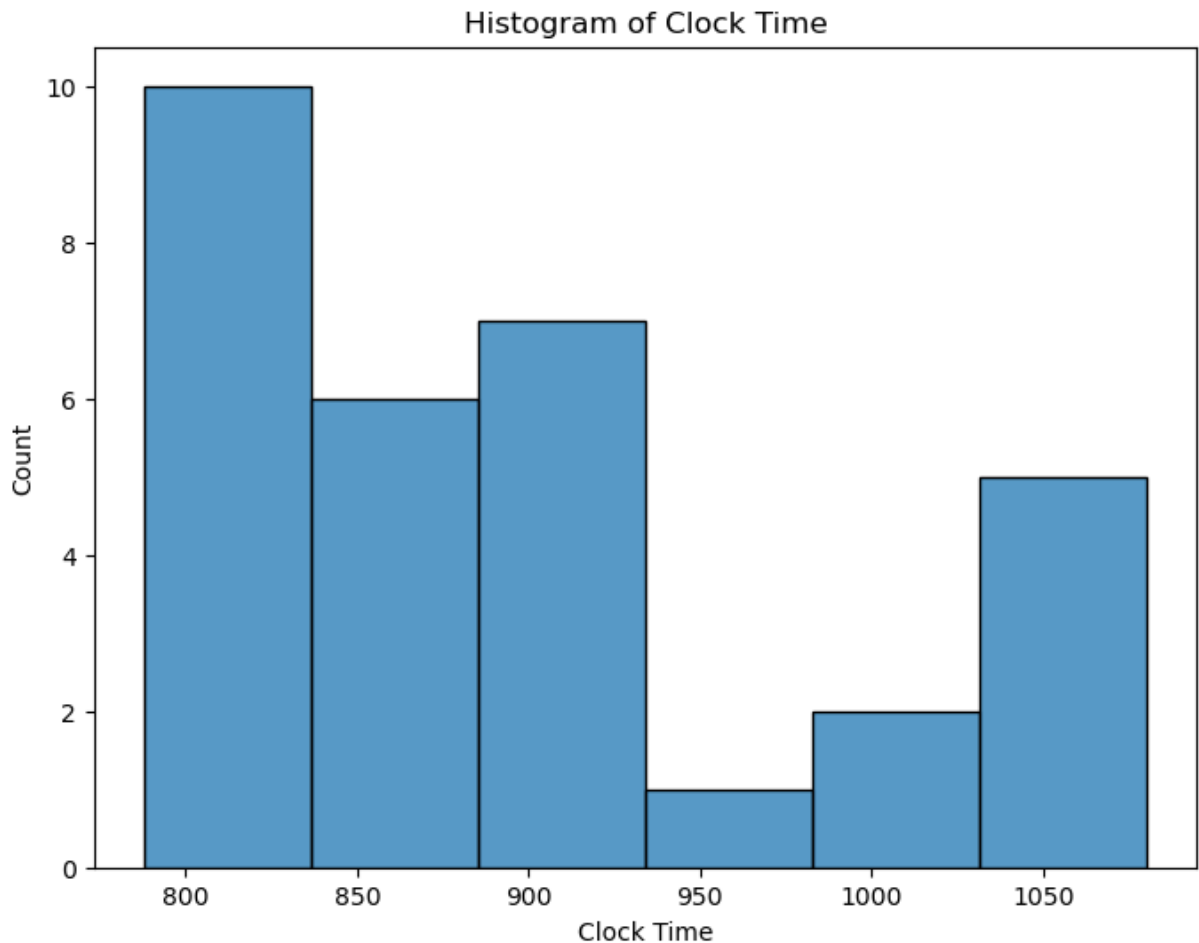
	Day	Pre 90 KMBAs Systolic	Pre 90 KMBAs Diastolic	\
count	31.000000	31.000000	31.000000	
mean	16.000000	133.548387	82.967742	
std	9.092121	5.909533	5.192840	
min	1.000000	124.000000	73.000000	
25%	8.500000	128.500000	79.000000	
50%	16.000000	134.000000	83.000000	
75%	23.500000	137.000000	85.000000	
max	31.000000	147.000000	96.000000	

	Pre 90 KMBAs Pulse	Post 90 KMBAs Systolic	Post 90 KMBAs Diastolic	\
count	31.000000	31.000000	31.000000	
mean	54.516129	138.193548	86.580645	
std	6.114851	5.918442	4.588204	
min	47.000000	126.000000	75.000000	
25%	51.000000	135.000000	84.000000	
50%	53.000000	139.000000	86.000000	
75%	57.500000	141.000000	89.500000	
max	74.000000	149.000000	96.000000	

	Post 90 KMBAs Pulse	Clock Time	Hour of Day
count	31.000000	31.000000	31.000000
mean	70.612903	898.064516	0.322581
std	5.070683	92.214581	0.475191
min	61.000000	788.000000	0.000000
25%	67.000000	831.000000	0.000000
50%	71.000000	878.000000	0.000000
75%	74.000000	935.000000	1.000000
max	82.000000	1080.000000	1.000000

In []: The range **from** "minimum" to "mean" Clock Time values may be a function of op when performing 90 KMBAs.

```
In [10]: # Histogram of "Clock Time"
plt.figure(figsize = (8, 6))
sns.histplot(data = Kinesthetics, x = 'Clock Time')
plt.xlabel('Clock Time')
plt.ylabel('Count')
plt.title('Histogram of Clock Time')
plt.show()
```

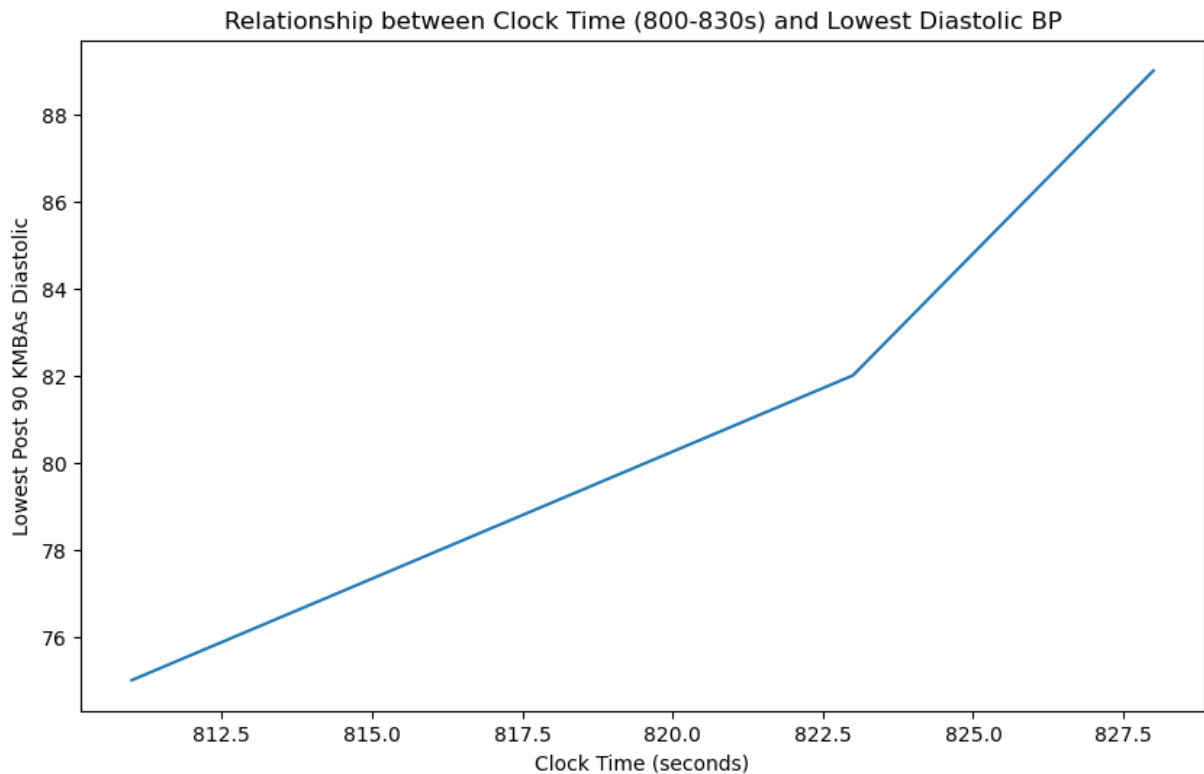


In []: Exploring the Clock Times having the highest count variability **and** whether t
blood pressure readings.
Below **is** a look at the diastolic numbers taken after performing **90** KMBAs.

```
In [11]: # Subsetting a dataset for Clock Times between 800 and 830 seconds
subset = Kinesthetics[(Kinesthetics['Clock Time'] >= 800) & (Kinesthetics['C

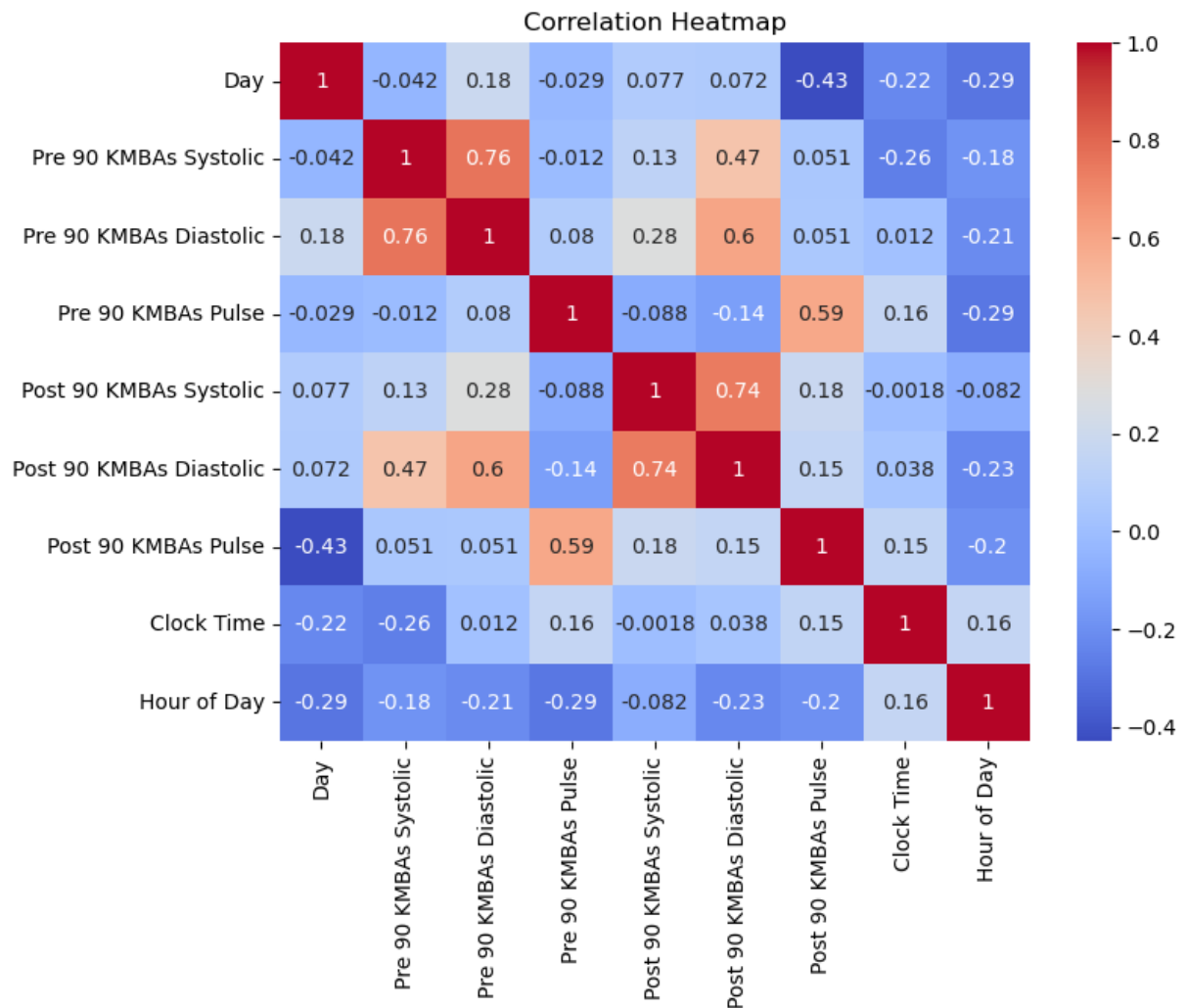
# Calculating minimum 'Post 90 KMBAs Diastolic' for this 'Clock Time' durati
min_diastolic = subset.groupby('Clock Time')['Post 90 KMBAs Diastolic'].min(

# Plotting the relationship
plt.figure(figsize=(10, 6))
plt.plot(min_diastolic.index, min_diastolic.values)
plt.xlabel('Clock Time (seconds)')
plt.ylabel('Lowest Post 90 KMBAs Diastolic')
plt.title('Relationship between Clock Time (800-830s) and Lowest Diastolic B
plt.show()
```



In []: To gather comprehensive trends/patterns in the dataset, a heatmap reveals the relationship between Pre 90 KMBA's Diastolic and Post 90 KMBA's Diastolic. A 60% likelihood that with increasing clock time, blood pressure increases. As for pulse rate, there is a 59% relationship between pre and post pulse rate.

```
In [12]: # Correlation Analysis and Heatmap
correlation_matrix = Kinesthetics.corr() #Calculating the correlation matrix
plt.figure(figsize = (8, 6))
sns.heatmap(correlation_matrix, annot = True, cmap = 'coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



In []: My hypothesis considered how 90 KMBAs could impact "ideal" blood pressure and movement had any aerobic/cardiovascular benefits. How significant the number could occur over a sustained period of time. I envisioned a model that could predict the optimal number of KMBAs to perfect resting heart rate, and blood pressure.

```
In [13]: # Data Visualization
plt.figure(figsize = (10, 6))
sns.scatterplot(x = 'Pre 90 KMBAs Diastolic', y = 'Post 90 KMBAs Diastolic',

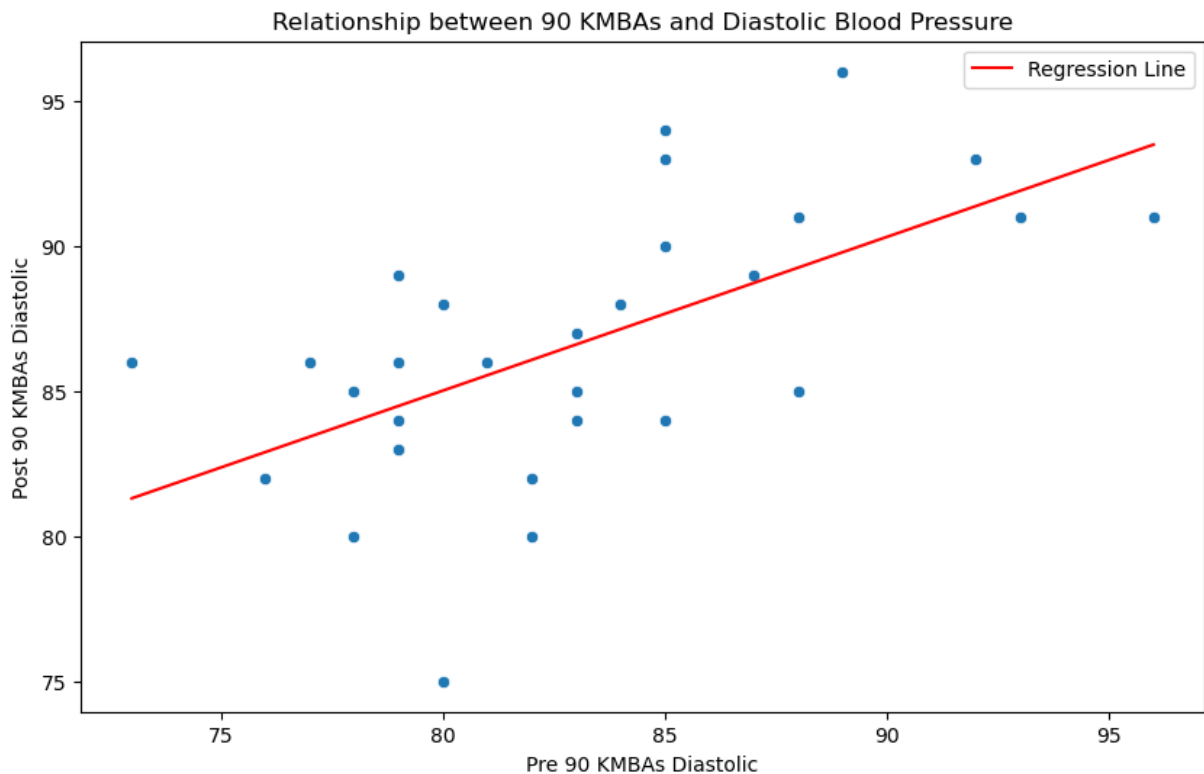
# Linear regression model
coefficients = np.polyfit(Kinesthetics['Pre 90 KMBAs Diastolic'], Kinesthetics['Post 90 KMBAs Diastolic'], 1)
intercept = coefficients[1]
slope = coefficients[0]

# Extrapolation
extrapolation_x = np.array([np.min(Kinesthetics['Pre 90 KMBAs Diastolic']), np.max(Kinesthetics['Pre 90 KMBAs Diastolic'])])
extrapolation_y = slope * extrapolation_x + intercept

# Regression line
plt.plot(extrapolation_x, extrapolation_y, color = 'red', label = 'Regression Line')

plt.xlabel('Pre 90 KMBAs Diastolic')
plt.ylabel('Post 90 KMBAs Diastolic')
```

```
plt.title('Relationship between 90 KMBAs and Diastolic Blood Pressure')
plt.legend()
plt.show()
```



```
In [16]: # Compute R-squared value
y_true = Kinesthetics['Post 90 KMBAs Diastolic']
y_pred = slope * Kinesthetics['Pre 90 KMBAs Diastolic'] + intercept
r2 = r2_score(y_true, y_pred)

print("R-squared:", r2)
```

R-squared: 0.3595234925465478

In []: In this model, attempting to predict diastolic blood pressure, I used: Pre 90 KMBAs Diastolic as the independent feature against the blood pressure reading after the 90 KMBAs. The resultant R-squared value of approximately 35.95% of the variance in the Post 90 KMBAs Diastolic is explained by the independent feature (Pre 90 KMBAs Diastolic).

R-squared values range from 0 to 1, where 1 represents a perfect fit and 0 represents no fit. In this scenario, the R-squared value of 0.3595 implies a moderate level of predictive power for predicting the Post 90 KMBAs Diastolic values.

Accordingly, it is important to keep in mind the limitations associated with this model, considering further experimentation with longer than the 31 days of observation.