NOVA IMS
Information Management School

Statistical Analysis

One-Way ANOVA Test for Social Media Use and Sleeping Patterns

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1. INTRODUCTION

Contextualization

Over the past decade, the world has experienced an explosion in the use of social media platforms, especially on mobile devices. Mobiles emit mostly blue light, and these wavelengths are particularly good at keeping us productive and focused. However, according to Newsom, Rob (2020), social media and sleep don’t mix well. The excessive use of social media can reduce sleep quality and increase the risk of a multitude of sleep issues.

Objectives

The main objective of this study is to analyse if the intensity of social media usage influences the number of hours of sleep using the One-Way Analysis of Variance (One-Way ANOVA) statistical method in Python (see appendix).

Limitations

It is important to mention that this is not a scientific experiment carried out by social media or sleep specialists, therefore one cannot assume that one variable causes the other. As wisely stated by Walton, Alice G. (2019), it could be the other way around: individuals who were already poor sleepers are on social media more as a result - or it could be another variable entirely that causes both the social media use and the sleep issues.

2. METHODOLOGY

In order to study if the intensity of social media usage influences the number of hours of sleep, four distinct groups of twenty individuals were selected. Each individual characterised their level of intensity of social media usage within four given categories: low, moderate, high, and very high usage. In addition, each one of them were asked about their average number of hours of sleep.

In order to make a confident and reliable decision, the One-Way ANOVA statistical technique was applied. This method has the fundamental purpose to test whether the means of the groups statistically differ from each other. In order to apply this test, the following assumptions must be validated:

ANOVA Assumptions:

1. The sample observations follow a continuous or ordinal distribution.
2. The sample observations are simple random (independent) samples.
3. The sample observations follow a normal distribution. Normality Test: Shapiro-Wilk.
4. The sample observations have homoscedasticity or homogeneity of variance. In other words, the variances of the samples are equal. Variance Test: Levene's.

To verify these assumptions, the following tests were performed: Shapiro-Wilk to test for normality, Levene's to test for homoscedasticity, followed by the ANOVA application itself and the post-hoc test Tukey-Kramer. The description of each test can be found below as well as their null and alternative hypothesis. Note that all tests are based on the 5% significance level, as per the example below (figure 1: Rejection Region), and the decisions were made taking the p-values into account rather than the observed and critical values.

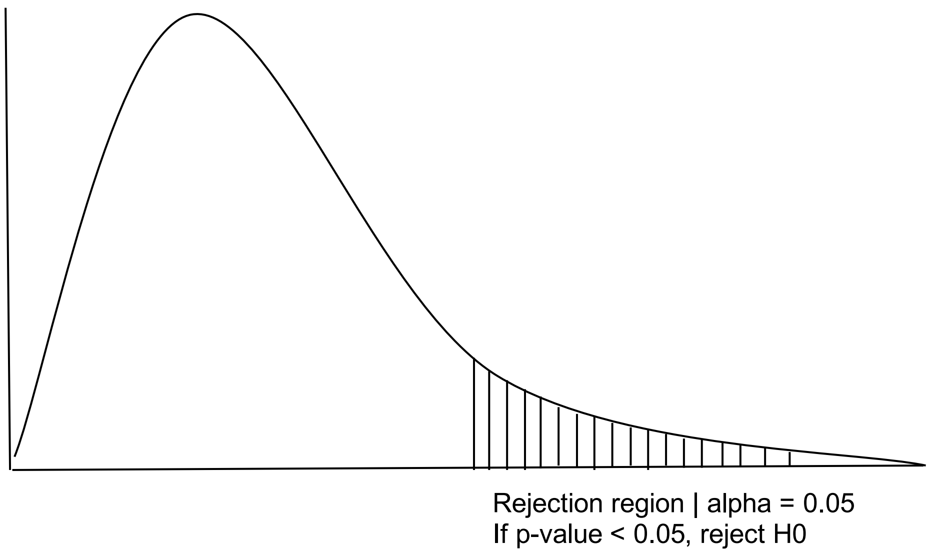

Figure 1: Rejection Region

Test for Normality - Shapiro-Wilk

According to Shapiro, S. S. & Wilk, M.B (1965), the Shapiro-Wilk tests the null hypothesis that the data was drawn from a normal distribution.

Hypothesis:

- ♦ H0 Null Hypothesis: $X \sim N(\mu, \sigma)$; the data is normally distributed.
- ♦ H1 Alternative Hypothesis: $X \neq N(\mu, \sigma)$; the data is not normally distributed.

Decision Rule:

- ♦ Reject H0 if $W_{Obs} < W_{Crit}$ | Reject H0 if p-value < 0.05.

Test for Homoscedasticity - Levene's Test

The Levene's test is an equal variance test. It can be used to check if our data sets fulfil the homogeneity of variance assumption before the Analysis of Variance (ANOVA) is tested (Htoon, Kyaw Saw. 2020).

Hypothesis:

- ♦ H0 Null Hypothesis: ${\sigma_1}^2 = {\sigma_2}^2 = {\sigma_3}^2 = {\sigma_4}^2$; variances are equal for all samples.
- ♦ H1 Alternative Hypothesis (H1): $\exists_{i,j(i \neq j)} \sigma_i^2 \neq \sigma_j^2$; variances are not equal for at least one pair.

Decision Rule:

- ♦ Reject H0 when $F_{Obs} \geq F_{(k-1,n-k,1-\alpha)}$ | Reject H0 if p-value < 0.05.

Analysis of Variance (ANOVA)

The one-way analysis of variance (ANOVA) is used to determine whether there are any statistically significant differences between the means of three or more independent unrelated groups (Statistics Laerd). A one-way ANOVA uses the following null and alternative hypotheses:

Hypothesis:

- ♦ H0 Null Hypothesis: $\mu_1 = \mu_2 = \mu_3 = \mu_4$; all the population means are equal.
- ♦ H1 Alternative Hypothesis: $\exists_{i,j(i \neq j)}: \mu_i \neq \mu_j$; at least one population mean is different.

Decision Rule (right-sided test):

- ♦ Reject H0 if $F_{obs} > F_{(k-1,n-k;1-\alpha)}$ | Reject H0 if p-value < 0.05.

Tukey-Kramer Test

The Tukey Test is a post-hoc test based on the studentized range distribution. An ANOVA test can tell if the results are significant overall, but it will not tell exactly where those differences lie. After the ANOVA is run, and found significant results, then a Tukey's HSD can be applied to find out which specific groups' means (compared with each other) are different. The test compares all possible pairs of means.

Hypothesis:

- H0 Null Hypothesis: $\mu_i = \mu_j \ (i \neq j)$; two populations have the same mean.
- H1 Alternative Hypothesis: $\mu_i \neq \mu_j \ (i \neq j)$; two populations do not have the same mean.

Decision Rule (right-sided test):

- Reject H0 when $W_{Obs} \geq q_{(k,n-k,1-\alpha)}$ | Reject H0 if p-value < 0.05

3. EXPLORATORY DATA ANALYSIS

Exploratory Data Analysis (EDA) is an approach to analysing data sets to summarise their main characteristics often using statistical graphs and other data visualisation methods. Through the process of EDA, one can get a better understanding of the dataset variables and the relationship between them, making it easier to discover patterns, detect outliers and anomalies, and test underlying assumptions.

The dataset under study is composed of a sample of 80 individuals who were asked how they would characterise their social media usage and average number of hours of sleep.

	count	mean	std	min	25%	50%	75%	max
Low Use	20.0	8.723411	0.486282	7.850318	8.447785	8.599661	8.967452	9.968084
Moderate Use	20.0	8.223411	0.486282	7.350318	7.947785	8.099661	8.467452	9.468084
High Use	20.0	7.420219	0.479335	6.559599	7.148531	7.298237	7.660774	8.647112
Very High Use	20.0	6.720219	0.479335	5.859599	6.448531	6.598237	6.960774	7.947112

Table 1: Statistical Description of the Dataset

Considering the statistical description of the dataset presented on the table above (Table 1: Statistical Description of the Dataset), it can be observed that the number of hours of sleep decreases as the usage of social media increases. To exemplify, a person who characterises their social media usage as low, sleeps on average 8.723 hours per night, while a person who states to have a very high usage of social media sleeps only 6.720 hours on average. This behaviour can be observed throughout the standard quartiles (25%, 50%, 75%) and minimum and maximum observed values, where people who spend more time on social media tend to sleep fewer hours.

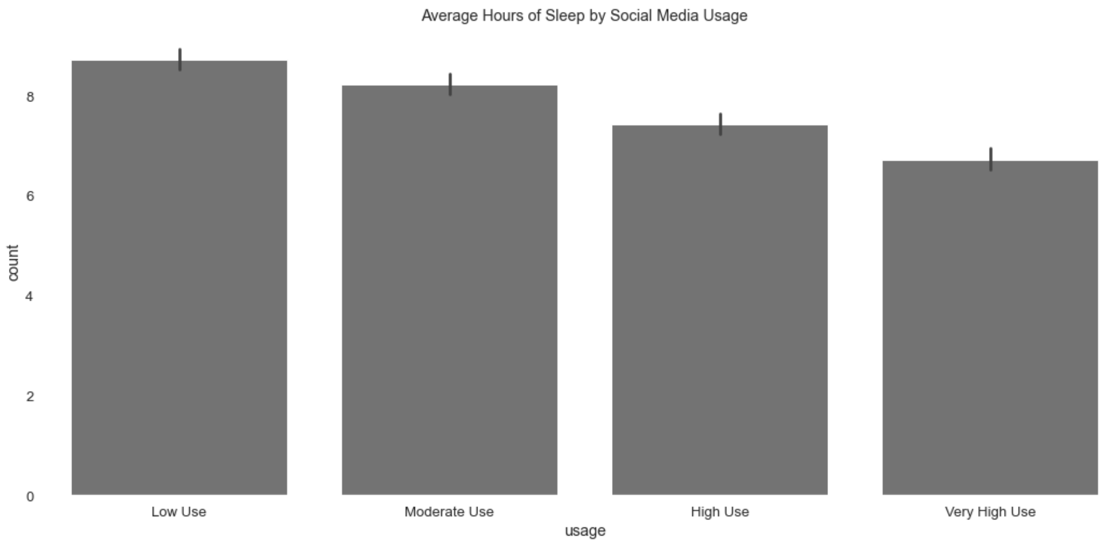

Figure 2: Average Hours of Sleep by Social Media Usage

The barplot represented on figure 2 above, is an easier way to visualise the results observed on the statistical description table (table 1), where the lowest the use of social media platforms is, the longest the individual tends to sleep. On the other hand, individuals who characterise their social media use as very high, tend to sleep less.

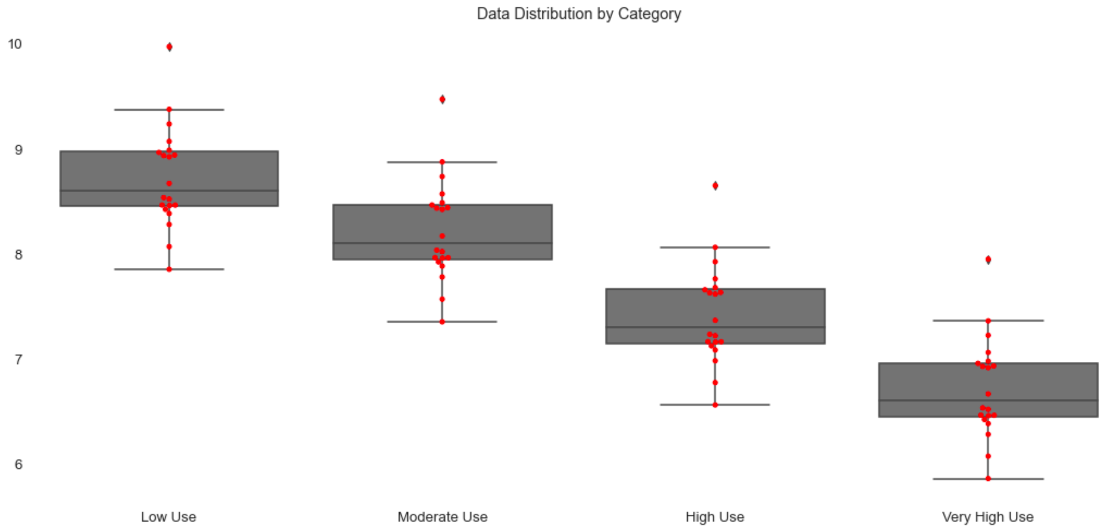

Figure 3: Data Distribution by Category

The boxplot (Figure 3: Data Distribution by Category) allows to easily detect the differences between social media usages and identify potential outliers. The red points represent each individual. We can observe that, in each group, most of the observations are concentrated in the lower and upper quartiles (Q1 and Q3), and that one outlier is present in each group. Since these outliers do not seem to be severe, this study will be carried out taking them into account.

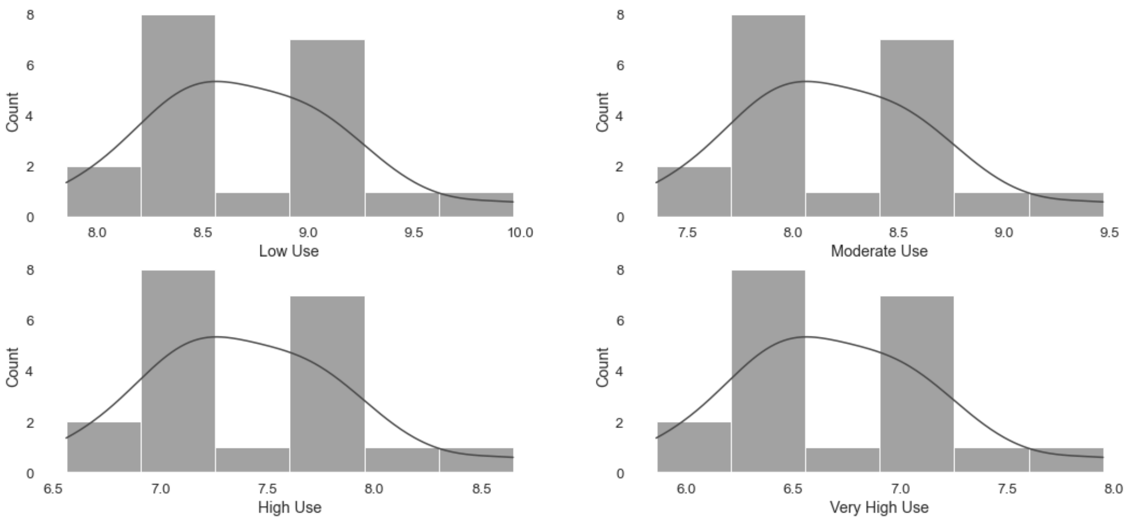

Figure 4: Histogram by Social Media Usage Category

The histograms presented on figure 4 show that the distribution of each group is approximately normal, however, a visual analysis is not enough to determine the symmetry of the distribution and formal tests must be applied.

4. RESULTS

As mentioned in chapter 2. Methodology, in order to apply the ANOVA method, the following assumptions must be tested: observations are independent, the distribution of the population is approximately symmetric, with the same variance. The results of the tests are described below.

4.1. Independence condition of the observations

As per the stakeholder statement, to conduct this study, an independent random sample of social media users was obtained, where each user can only belong to one group. Based on this affirmation, it can be assumed that the observations are independent.

4.2 Distribution Fitting Test

The Shapiro-Wilk test was applied to test the normality of the distribution using the library scipy.stats (Scipy Stats, shown on figure 5) and the results obtained are shown below on table 2.

```python
# Shapiro-Wilk test for each variable individually
def shapiro_test(variable):
    shapiro_test = stats.shapiro(df[variable])
    print(variable, ': ', shapiro_test)

shapiro_test('Low Use')
shapiro_test('Moderate Use')
shapiro_test('High Use')
shapiro_test('Very High Use')
```

Figure 5: Shapiro-Wilk Test using the Scipy library in Python

Output table (table 2: Shapiro-Wilk Test Results):

Category	Statistic	p-value
Low Use	0.956627	0.478869
Moderate Use	0.956627	0.478870
High Use	0.956627	0.478870
Very High Use	0.956627	0.478870

Table 2: Shapiro-Wilk Test Results

Result: The Shapiro-Wilk test p-value is greater than α = 0.05, therefore failing to reject H0.
Conclusion: There is enough evidence to conclude that the data is normally distributed at a 5% significance level.

4.3 Tests for Homoscedasticity

The Levene's test was applied to test the equality of the variances (figure 6) through the bioinfokit library in Python.

```
res = stat()
res.levene(df=df_melt, res_var='count', xfac_var='usage')
res.levene_summary
```

Figure 6: Levene's using the bioinfokit library in Python

Output table (table 3: Levene's Test Results):

Parameter	Value
Test statistics (W)	0.0020
Degrees of freedom (Df)	3.0000
p-value	0.9999

Table 3: Levene's Test Results

Result: The Levene's test p-value is greater than α = 0.05, therefore failing to reject H0.
Conclusion: There is strong evidence that the variances are equal across all samples at 5% confidence level.

4.4 Analysis of Variance

The Analysis of Variance (ANOVA) technique was applied (figure 6) using the bioinfokit library in Python.

```
# ANOVA table using bioinfokit v1.0.3 or later (it uses wrapper script for anova_lm)
res = stat()
res.anova_stat(df=df_melt, res_var='count', anova_model='count ~ C(usage)')
res.anova_summary
```

Figure 7: Analysis of Variance using the bioinfokit library in Python

Output table (table 4: Analysis of Variance Test Results):

	df	sum_sq	mean_sq	F	PR(>F
C(usage) | Between	3.0	46.778932	15.592977	66.889431	2.853701e-21
Residual | Within	76.0	17.716794	0.233116		

Table 4: Analysis of Variance Test Results

Result: The ANOVA p-value is lower than α = 0.05, therefore H0 is rejected.
Conclusion: It can be concluded that, statistically, there are significant differences among the usage of social media and the average sleep time. However, using this analysis, it is not possible to indicate which ones, out of the four samples, have significant differences. Therefore, a post-hoc test needs to be applied.

4.5 Tukey-Kramer Test

The Tukey-Kramer test was applied (Figure 8: Tukey-Kramer Test Result) using the bioinfokit library in Python (Bedre, Renesh. 2020).

```
# we will use bioinfokit (v1.0.3 or later) for performing tukey HSD test
# check documentation here https://github.com/reneshbedre/bioinfokit

# perform multiple pairwise comparison (Tukey's HSD)
# unequal sample size data, tukey_hsd uses Tukey-Kramer test
res = stat()
res.tukey_hsd(df=df_melt, res_var='count', xfac_var='usage', anova_model='count ~ C(usage)')
res.tukey_summary
```

Figure 8: Tukey-Kramer Test using the bioinfokit library in Python

Output table (table 5: Tukey-Kramer Test Result):

	group1	group2	Diff	Lower	Upper	q-value	p-value
0	Low Use	Moderate Use	0.500000	0.098924	0.901076	4.631261	0.008491
1	Low Use	High Use	1.303192	0.902115	1.704268	12.070840	0.001000
2	Low Use	Very High Use	2.003192	1.602115	2.404268	18.554605	0.001000
3	Moderate Use	High Use	0.803192	0.402115	1.204268	7.439579	0.001000
4	Moderate Use	Very High Use	1.503192	1.102115	1.904268	13.923344	0.001000
5	High Use	Very High Use	0.700000	0.298924	1.101076	6.483765	0.001000

Table 5: Tukey-Kramer Test Results

Result: The Tukey-Kramer test p-values are lower than α = 0.05 for all pairwise comparisons, therefore H0 is rejected.
Conclusion: It can be concluded that there are statistically significant differences between all the average hours of sleep of each group.

5. CONCLUSION

According to some specialists, the intensity of social media usage can affect the quality of sleep of an individual. In order to test this statement, a group of eighty individuals have characterised their social media usage and average hours of sleep. The dataset with the results was provided for analysis.

The Analysis of Variance was the method chosen to compare the means of each group and identify if there is a statistically significant difference between them. The results obtained suggest that the means are statistically significant, which evidences that the intensity of social media usage does affect the average hours of sleep of an individual.

However, it is important to reinforce that this is not a causality study, meaning that the average time spent on social media may not have not caused individuals to sleep more (or less). It could be the other way around or even another variable entirely that causes both the social media use and the sleep issues.

6. BIBLIOGRAPHY

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Shapiro, S. S. & Wilk, M.B (1965). An analysis of variance test for normality (complete samples), Biometrika, Vol. 52, pp. 591-611.

Walton, Alice G. (2019, October 24th) Social Media Use May Mess With Teens' Sleep. Available on <https://www.forbes.com/sites/alicegwalton/2019/10/24 /heavy-social-media-use-may-steal-teens-sleep/?sh=b0c031769bf4>.

APPENDIX

One-Way ANOVA Test for Social Media Use and Sleeping Patterns

Contextualization

Over the past decade, the world has experienced an explosion in the use of social media platforms, especially on mobile devices. Mobiles emit mostly blue light, and these wavelengths are particularly good at keeping us productive and focused. However, according to Newsom, Rob (2020), social media and sleep don't mix well. The excessive use of social media can reduce sleep quality and increase the risk of a multitude of sleep issues.

Objectives

The main objective of this study is to analyse if the intensity of social media usage influences the number of hours of sleep using the One-Way Analysis of Variance (One-Way ANOVA) statistical method in Python.

Limitations

It is important to mention that this is not a scientific experiment carried out by social media or sleep specialists, therefore one cannot assume that one variable causes the other. As wisely stated by Walton, Alice G. (2019), it could be the other way around: individuals who were already poor sleepers are on social media more as a result - or it could be another variable entirely that causes both the social media use and the sleep issues.

Importing the Dataset and Libraries

In [2]:

```
# importing libraries that will be used in this project
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import scipy.stats as stats
from distfit import distfit
from bioinfokit.analys import stat
import statsmodels.api as sm
from statsmodels.formula.api import ols
from scipy.stats import bartlett
import warnings

%matplotlib inline
warnings.filterwarnings("ignore")
```

In [3]:

```
# seaborn charts decoration
sns.set(rc={'figure.figsize':(10,5)}, font_scale=1.2)
sns.set_style({'axes.facecolor':'white', 'grid.color': 'white'})
```

Data Visualization

In [4]:

```
# importing dataset
df = pd.read_csv("Series24.csv")
```

In [5]:

```
# visualizing the first 5 rows of the dataset
df.head()
```

Out[5]:

	Low Use	Moderate Use	High Use	Very High Use
0	8.983252	8.483252	7.676349	6.976349
1	8.420320	7.920320	7.121458	6.421458
2	8.962186	8.462186	7.655583	6.955583
3	7.850318	7.350318	6.559599	5.859599
4	9.372347	8.872347	8.059885	7.359885

This table provides an initial idea of the dataset used in this project.

In [6]:

```
# display a concise summary of the dataset
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20 entries, 0 to 19
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Low Use        20 non-null     float64
 1   Moderate Use   20 non-null     float64
 2   High Use       20 non-null     float64
 3   Very High Use  20 non-null     float64
dtypes: float64(4)
memory usage: 768.0 bytes
```

This table gives more information related to the variables and their formats.

Exploratory Data Analysis

In [7]:

```
# statistical description of the dataset
df.describe(include='all').T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
Low Use	20.0	8.723411	0.486282	7.850318	8.447785	8.599661	8.967452	9.968084
Moderate Use	20.0	8.223411	0.486282	7.350318	7.947785	8.099661	8.467452	9.468084
High Use	20.0	7.420219	0.479335	6.559599	7.148531	7.298237	7.660774	8.647112
Very High Use	20.0	6.720219	0.479335	5.859599	6.448531	6.598237	6.960774	7.947112

Considering the statistical description of the dataset presented on the table above, it can be observed that the number of hours of sleep decreases as the usage of social media increases. To exemplify, a person who characterises their social media usage as low, sleeps on average 8.723 hours per night, while a person who states to have a very high usage of social media sleeps only 6.720 hours on average. This behaviour can be observed throughout the standard quartiles (25%, 50%, 75%) and minimum and maximum observed values, where people who spend more time on social media tend to sleep fewer hours.

In [8]:

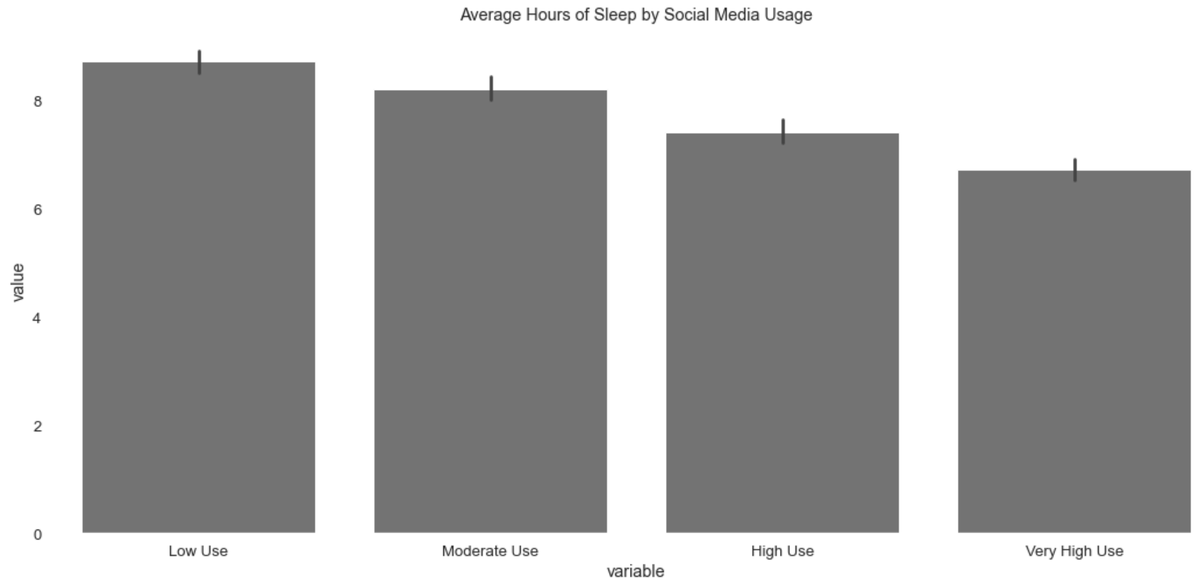
```
# reshape the d dataframe suitable for statsmodels package
df_melt = pd.melt(df.reset_index(), id_vars=['index'],
value_vars=['Low Use', 'Moderate Use', 'High Use',

'Very High Use'])
# Make the plot
fig, ax = plt.subplots(figsize=(18,8))
sns.barplot(x=df_melt['variable'],y=df_melt['value'],data =
df_melt,color='#737373')
plt.title('Average Hours of Sleep by Social Media Usage')
    index       variable     value
0       0        Low Use  8.983252
1       1        Low Use  8.420320
2       2        Low Use  8.962186
3       3        Low Use  7.850318
4       4        Low Use  9.372347
..    ...            ...       ...
75     15  Very High Use  6.072463
76     16  Very High Use  6.280276
77     17  Very High Use  6.664693
78     18  Very High Use  7.947112
79     19  Very High Use  6.457555

[80 rows x 3 columns]
```

Out[8]:

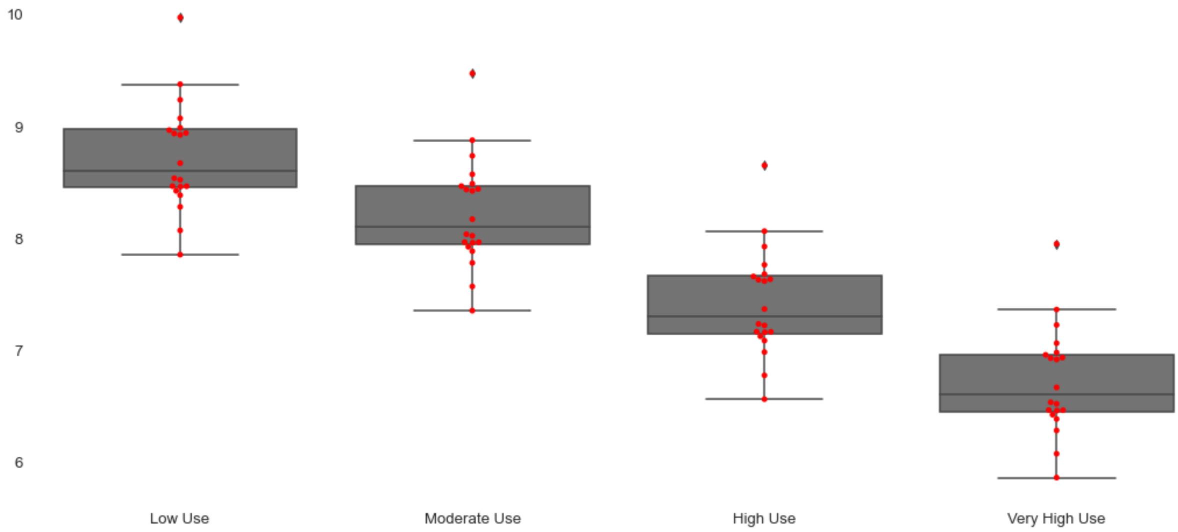
```
Text(0.5, 1.0, 'Average Hours of Sleep by Social Media Usage')
```



The barplot represented on figure above, provides an easy way to visualise the results observed on the statistical description table where the lowest the use of social media platforms is, the longest the individual tends to sleep. On the other hand, individuals who characterise their social media use as very high, tend to sleep less.

In [10]:

```
# generate a boxplot to see the data distribution by usage. Using
boxplot, we can
# easily detect the differences between different social media usage
fig, ax = plt.subplots(figsize=(18,8))
ax = sns.boxplot(data=df, color='#737373')
ax = sns.swarmplot(data=df, color='red')
plt.show()
```



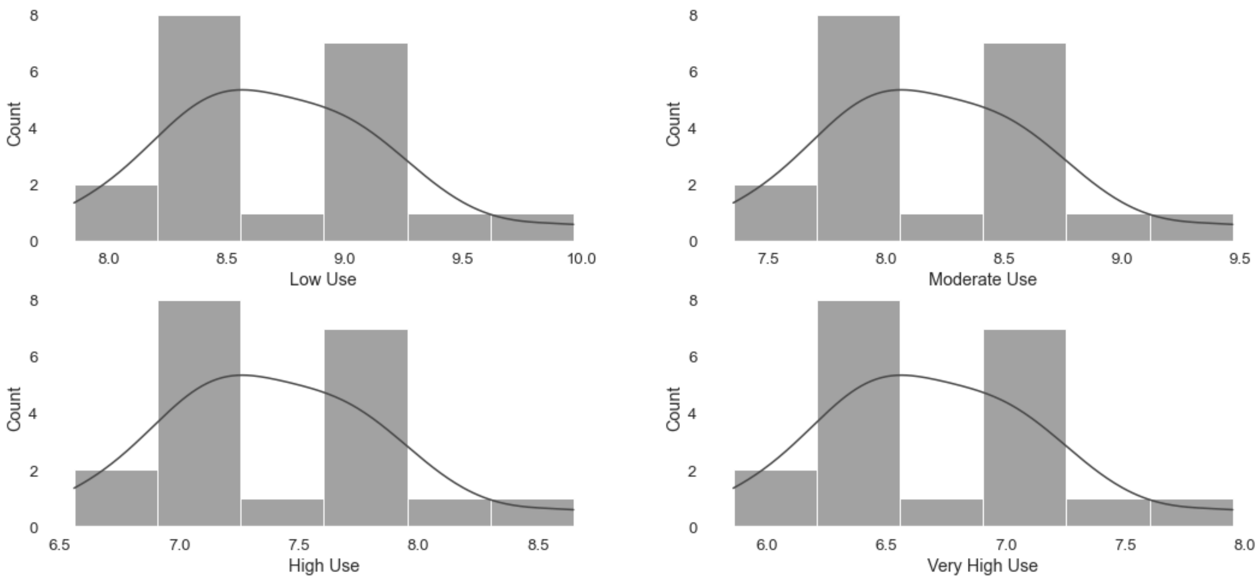
The boxplot above allows to easily detect the differences between social media usages and identify potential outliers. The red points represent each individual. We can observe that, in each group, most of the observations are concentrated in the lower and upper quartiles (Q1 and Q3), and that one outlier is present in each group. Since these outliers are not severe, this study will be carried out taking them into account.

In [9]:

```
# HISTOGRAM (ALL NUMERIC VARIABLES)

# Identify all numeric variables in the dataset
numerical=df.select_dtypes(include=[np.number]).columns.tolist()

# Draw
fig, ax = plt.subplots(2, 2, figsize=(18,8))
for var, subplot in zip(df[numerical], ax.flatten()):
    g =sns.histplot(data=df,x=var,ax=subplot,kde=True,color='#474747')
```



The histograms presented on figure 4 show that the distribution of each group is approximately normal, however, a visual analysis is not enough to determine the symmetry of the distribution and formal tests must be applied.

Distribution Fitting Test

The Shapiro-Wilk test was applied to test the normality of the distribution using the library scipy.stats (Scipy Stats) and the results obtained are shown below on table 2.

In [11]:

```
# Shapiro-Wilk test for variables altogether
shapiro_test = stats.shapiro(df)
print('Result: ', shapiro_test)
Result:  ShapiroResult(statistic=0.9829710721969604,
pvalue=0.3662208616733551)
```

In [12]:

```
# Shapiro-Wilk test for each variable individually
def shapiro_test(variable):
    shapiro_test = stats.shapiro(df[variable])
    print(variable, ': ', shapiro_test)
```

```
shapiro_test('Low Use')
shapiro_test('Moderate Use')
shapiro_test('High Use')
shapiro_test('Very High Use')
Low Use :  ShapiroResult(statistic=0.9566276669502258,
pvalue=0.4788699448108673)
Moderate Use :  ShapiroResult(statistic=0.9566276669502258,
pvalue=0.47887012362480164)
High Use :  ShapiroResult(statistic=0.9566276669502258,
pvalue=0.47887012362480164)
Very High Use :  ShapiroResult(statistic=0.9566276669502258,
pvalue=0.47887012362480164)
```

Result: The Shapiro-Wilk test p-value is greater than α = 0.05, therefore failing to reject H0.
Conclusion: There is enough evidence to conclude that the data is normally distributed at a 5% significance level.

Tests for Equality of Variances (Homoscedasticity)

The Levene's test was applied to test the equality of the variances (figure 6) through the bioinfokit library in Python.

In [ ]:

```
# re-definining some dataset properties before applying the test
df_melt.columns = ['index', 'usage', 'count']
```

In [13]:

```
# initializing the test
res = stat()
res.levene(df=df_melt, res_var='count', xfac_var='usage')
res.levene_summary
```

Out[13]:

	Parameter	Value
0	Test statistics (W)	0.0020
1	Degrees of freedom (Df)	3.0000
2	p value	0.9999

Result: The Levene's test p-value is greater than α = 0.05, therefore failing to reject H0.
Conclusion: There is strong evidence that the variances are equal across all samples at 5% confidence level.

Analysis of Variance (ANOVA)

The Analysis of Variance (ANOVA) technique was applied using the bioinfokit library in Python.

In [15]:

```
# ANOVA table using bioinfokit v1.0.3 or later (it uses wrapper script
for anova_lm)
res = stat()
res.anova_stat(df=df_melt, res_var='count', anova_model='count ~
C(usage)')
res.anova_summary
```

Out[15]:

	df	sum_sq	mean_sq	F	PR(>F)
C(usage)	3.0	46.778932	15.592977	66.889431	2.853701e-21
Residual	76.0	17.716794	0.233116	NaN	NaN

Result: The ANOVA p-value is lower than α = 0.05, therefore H0 is rejected.
Conclusion: It can be concluded that there are significant differences among the usage of social media and the average sleep time.

Multiple comparison tests

The Tukey-Kramer test was applied (figure 8) using the bioinfokit library in Python (Bedre, Renesh. 2020).

In [16]:

```
# we will use bioinfokit (v1.0.3 or later) for performing tukey HSD
test
# check documentation here https://github.com/reneshbedre/bioinfokit

# perform multiple pairwise comparison (Tukey's HSD)
# unequal sample size data, tukey_hsd uses Tukey-Kramer test
res = stat()
res.tukey_hsd(df=df_melt, res_var='count', xfac_var='usage',
anova_model='count ~ C(usage)')
res.tukey_summary
```

Out[16]:

	group1	group2	Diff	Lower	Upper	q-value	p-value
0	Low Use	Moderate Use	0.500000	0.098924	0.901076	4.631261	0.008491
1	Low Use	High Use	1.303192	0.902115	1.704268	12.070840	0.001000
2	Low Use	Very High Use	2.003192	1.602115	2.404268	18.554605	0.001000

	group1	group2	Diff	Lower	Upper	q-value	p-value
3	Moderate Use	High Use	0.803192	0.402115	1.204268	7.439579	0.001000
4	Moderate Use	Very High Use	1.503192	1.102115	1.904268	13.923344	0.001000
5	High Use	Very High Use	0.700000	0.298924	1.101076	6.483765	0.001000

Result: The Tukey-Kramer test p-values are lower than $\alpha = 0.05$ for all pairwise comparisons, therefore H0 is rejected.
Conclusion: It can be concluded that there are statistical significant differences between the average hours of sleep of each group.

Conclusion

According to some specialists, the intensity of social media usage can affect the quality of sleep of an individual. In order to test this statement, a group of eighty individuals have characterised their social media usage and average hours of sleep. A dataset with the results was provided for analysis. Considering the Analysis of Variance (One-Way ANOVA) results, it can be concluded that there is evidence that the intensity of social media usage does affect the average hours of sleep of an individual.

In [ ]: