

## HW3: Experiment Analysis Report

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### Part 1: Getting to know your data

#### 1. What data is in the file "t1\_users\_active\_mins.csv"?

This file contains data about the users' active minutes after the experiment started. It has three columns: uid, dt, and active\_mins. Each row represents the total active minutes(active\_mins) spent by a user(uid) on a specific date (dt) after the experiment began. If a user does not visit the site on a given date, they will not have an entry for that date.

#### 2. What data is in file "t2\_users\_variant.csv"?

This file contains data about the users' treatment assignments. It has four columns: uid, variant\_number, dt, and signup\_date. Every user belongs to either the control group(variant\_number=0) or the treatment group(variant\_number=1). Each row represents the experiment assignment of a unique user. The column 'dt' is 2019-02-06 for all users, while 'signup\_date' varies per user.

#### 3. What data is in file "t3\_users\_active\_mins\_pre.csv"?

This file contains data about the users' active minutes before the experiment started. It has the same structure as "t1\_users\_active\_mins.csv," with three columns: uid, dt, and active\_mins. However, the dates in this file (dt) are from before the experiment started. This will help us compare user activity before and after the update.

#### 4. What data is in file "t4\_users\_attributes.csv"?

This file contains data about some user attributes. It has three columns: uid, gender, and user\_type. Each row represents a unique user's attributes, such as gender and activity level ('new\_user', 'non\_reader', 'reader', or 'contributor').

#### 5. What data is in file "table\_schema.txt"?

This file explains the structure of all the dataset files and helps us understand what each column represents.

### Part 2: Organizing the Data

The overall objective of this study is to see if the new layout increases user engagement. For this, we need data on how long users stay active and which group they are in (control or treatment). The file *t1\_user\_active\_min.csv* has user activity but doesn't say which group a user belongs to. That information is in *t2\_user\_variant.csv*, so I have merged both files using *uid*. The final dataset is now structured with userID, date, active minutes, and experiment group and ready for statistical analysis.

Merged Dataset:

	uid	dt	active_mins	variant_number
0	0	2019-02-22	5.0	0
1	0	2019-03-11	5.0	0
2	0	2019-03-18	3.0	0
3	0	2019-03-22	4.0	0
4	0	2019-04-03	9.0	0

### Part 3: Statistical Analysis

Control Group (A) = Users who did not receive the new platform update.

Treatment Group (B) = Users who received the new platform update.

Metric = Total active minutes spent on the platform.

Let's now perform hypothesis testing to check if the update significantly increased engagement.

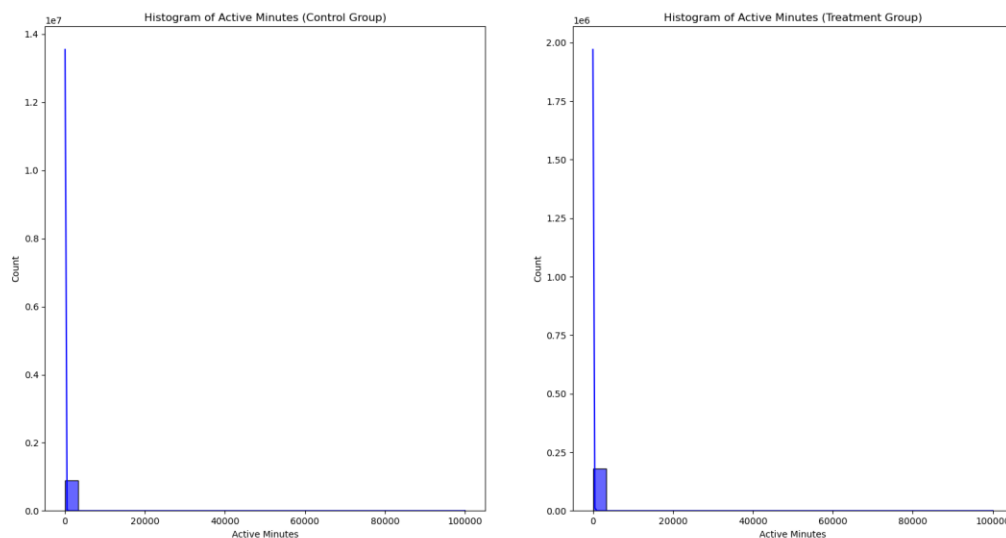
**Null Hypothesis:** The new platform update does not increase active minutes.

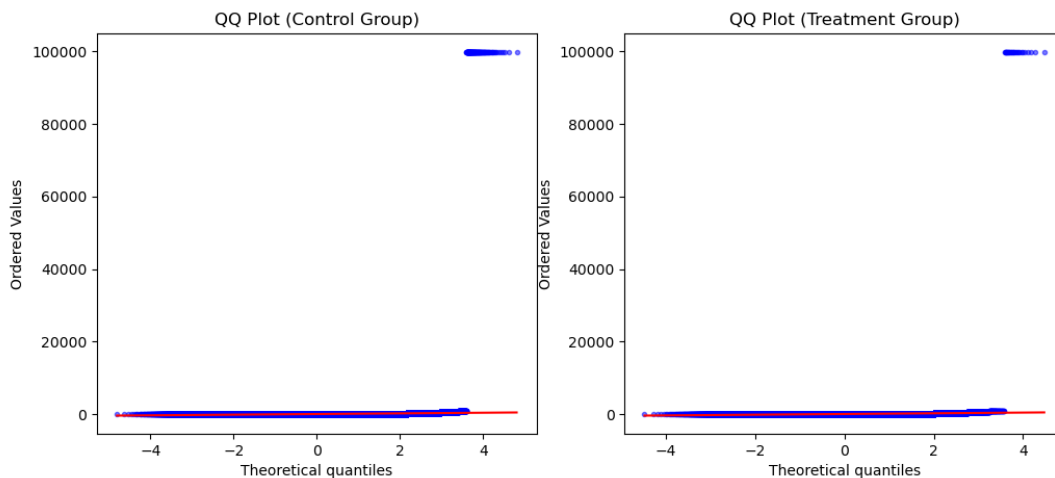
**Alternative Hypothesis:** The new platform update does increase active minutes.

Let's set  $\alpha = 0.05$ . If p-value < 0.05, we will reject the Null Hypothesis and conclude that the update improved engagement.

Now, let's check whether our data is distributed normally by plotting Histogram and QQ plots.

If it is normal, we will use a T-test; otherwise, we will use a Mann-Whitney U-Test.





The histograms show a right-skewed distribution and also the QQ plots indicate that the data is not normally distributed. Therefore, we will use the Mann-Whitney U-Test instead of T-test.

```
Mann-Whitney U-Test Results:
MannwhitneyuResult(statistic=np.float64(70467369895.5), pvalue=np.float64(0.0))
```

The results of the Mann-Whitney U-Test shows that p-value is less than 0.05, so we reject the Null Hypothesis. This means the new platform significantly increased user engagement.

### 1. Is there a static difference between group 1 and group 2?

Yes, there is a significant difference. The p-value = 0.0 which is less than 0.05, so we reject the Null Hypothesis.

This means the new platform significantly increased user engagement.

### 2. What is the mean and median for group 1 and group 2?

The treatment group (new platform) shows a higher average and median active time compared to the control group. However, the high variance and standard deviation suggest that the data has large fluctuations. This indicates the presence of outliers that might be skewing the results.

variant_number	mean	median	std	var
0	35.344199	5.0	1265.733184	1.602080e+06
1	40.240408	7.0	1293.703072	1.673668e+06

### 3. What can you conclude based on that data?

The treatment group has higher active minutes than the control group, suggesting that the new platform is encouraging users to stay longer. The p-value is statistically significant (0.0), so we reject the Null Hypothesis.

However, the high variance and standard deviation as well graphs indicate the presence of outliers, which may be affecting the results.

## Part 4: Digging a Little Deeper

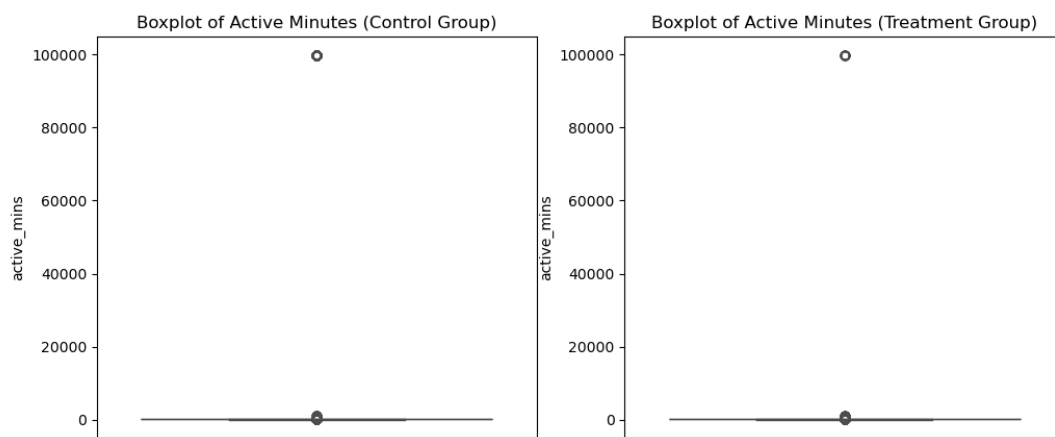
### 1. Can you trust that the results? Why or why not?

No, we cannot trust our results in Part3 because we noticed that some users have extremely high active minutes, which means outliers. Outliers can distort the mean and give misleading results. Hence, before making a final conclusion, we need to check if removing these outliers changes our conclusion.

### 2. Is the data normally distributed?

No, the data is not normally distributed. We already checked this in Part 3 by plotting histograms and QQ plots. The histograms show right-skewed distributions with long tails. The QQ plots also confirmed that data is not normally distributed.

### 3. Plot a box plot of group 1 and group 2.



### 4. Are there any outliers?

Yes! The boxplots confirm that there are many outliers in both the control and treatment groups. Some users have active minutes exceeding 1,440 per day, which is impossible because a day has only 1,440 minutes. So, they should be considered as outliers.

### 5. What might be causing those outliers?

These outliers might be caused by data entry errors or by some automated systems like bots. Theoretically, no user should have more than 1,440 minutes in a day (because 1,440 minutes = 24 hours).

### 6. Remove any data point that might be causing outliers.

We will filter out users with more than 1,440 active minutes per day and see how many outliers are removed. Even 1,440 active minutes per day is also unusual, but there may be some folks who are addicted to the new feature, so we can't take a risk by removing it.

```
Outliers removed: 172
Max Active Minutes After Outlier Removal: 897.0
```

A total of 172 extreme outliers were removed from the data.

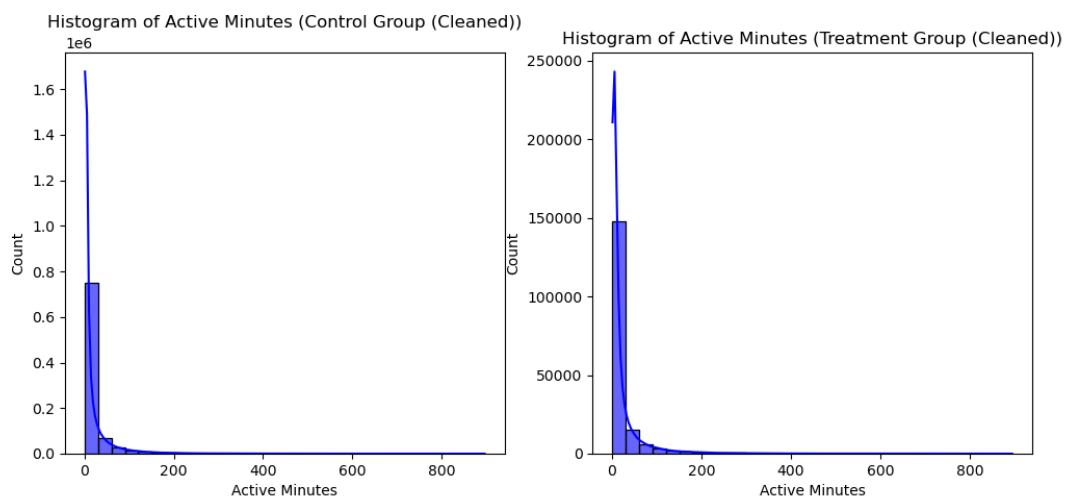
## 7. Redo part 2 and 3 with the new data without those data points.

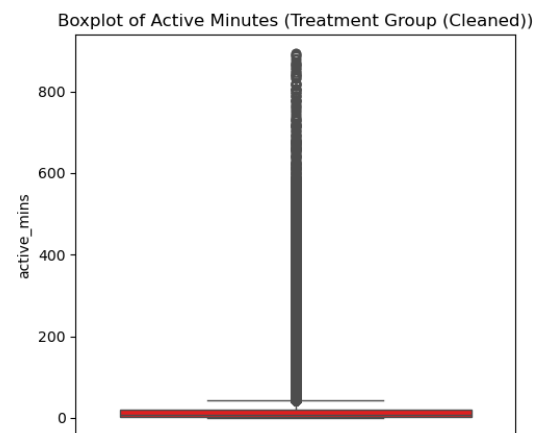
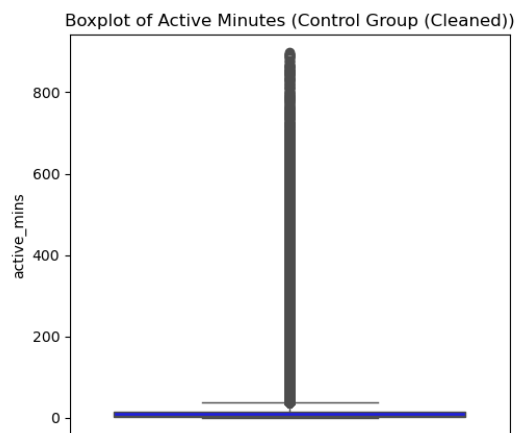
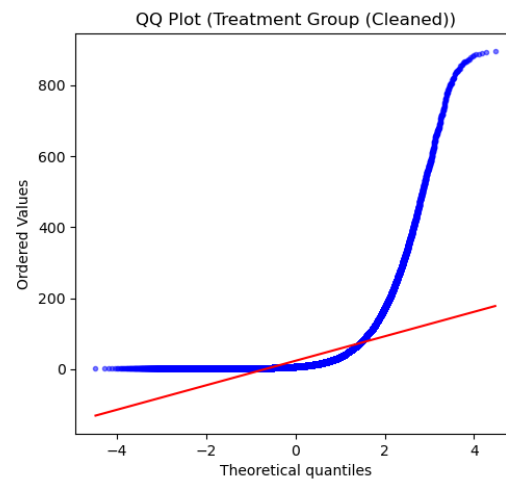
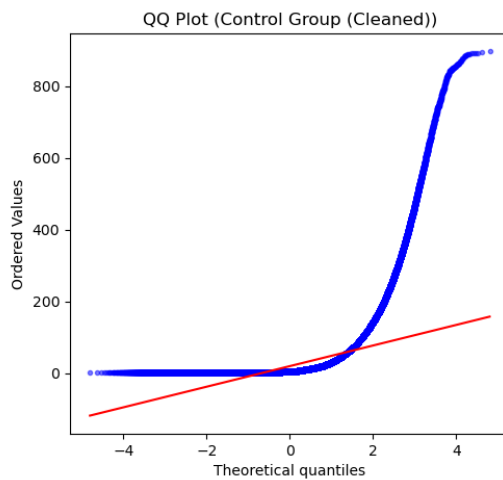
Now that we have removed the outliers, let's recompute the mean and median.

	Control	Treatment
Mean	19.337660	23.526294
Median	5.000000	7.000000
Std Dev	44.797631	54.191356
Variance	2006.827734	2936.703110

The treatment group still has a higher mean and median than the control group.

Let's again check normality of data by plotting histogram, and boxplots.





The histograms , QQ plots and box plots indicate that the data is not normally distributed. Therefore, we will use the Mann-Whitney U-Test.

```
Mann-Whitney U-Test Results:
MannwhitneyuResult(statistic=np.float64(70441890835.5), pvalue=np.float64(0.0))
```

The Mann-Whitney U-Test still resulted in p-value = 0.0.

## 8. What is the new conclusion based on the new data?

In Part 3, before removing outliers, the Treatment group had significantly higher engagement (p-value = 0.0).

However, even after removing outliers, the p-value remains 0.0, meaning the difference is still statistically significant.

This means the new platform update has significantly improved engagement.

## Part 5: Digging Even Deeper

### 1. Why do we care about the data from t3?

We care about this file because it contains user engagement before the experiment started. We need to check if the treatment and control groups were equal before the update. If one group was already using the platform less, then their increase in engagement might not be fully caused by the update.

### 2. Accounting for the data from t3 rerun part 2 and 3.

- Merged t3\_user\_active\_min\_pre.csv (pre-experiment data) with t2\_user\_variant.csv (user assignments)

This allowed us to see which users were in the control and treatment groups before the update.

Merged Dataset:

	uid	dt	active_mins	variant_number
0	0	2018-09-24	3.0	0
1	0	2018-11-08	4.0	0
2	0	2018-11-24	3.0	0
3	0	2018-11-28	6.0	0
4	0	2018-12-02	6.0	0

- Removed outliers (users with more than 1,440 active minutes in a single day).

This ensured our pre-experiment data was clean and realistic.

Outliers removed: 166  
Max Active Minutes After Outlier Removal: 897.0

- Added up total pre-experiment active minutes per user  
Instead of looking at daily data, we calculated total minutes spent by each user before the experiment.
- Compared the control and treatment groups before the update
  - We calculated average (mean) and median active minutes for both groups.
  - We performed a Mann-Whitney U-Test to check if the groups were different before the update.
  - We calculated engagement gain (post-experiment minutes - pre-experiment minutes) to measure how much each group's engagement changed after the update.

Summary Statistics for Pre-Experiment Engagement:

	count	mean	std	min	25%	50%	75%	max
variant_number								
0	39776.0	477.659946	1820.584432	1.0	18.0	55.0	191.0	47307.0
1	9921.0	274.721097	1078.118840	1.0	15.0	45.0	140.0	39077.0

Mann-Whitney U-Test Result (Pre-Experiment Engagement): MannwhitneyUResult(statistic=np.float64(212963286.0), pvalue=np.float64(1.7692641504649626e-34))

```

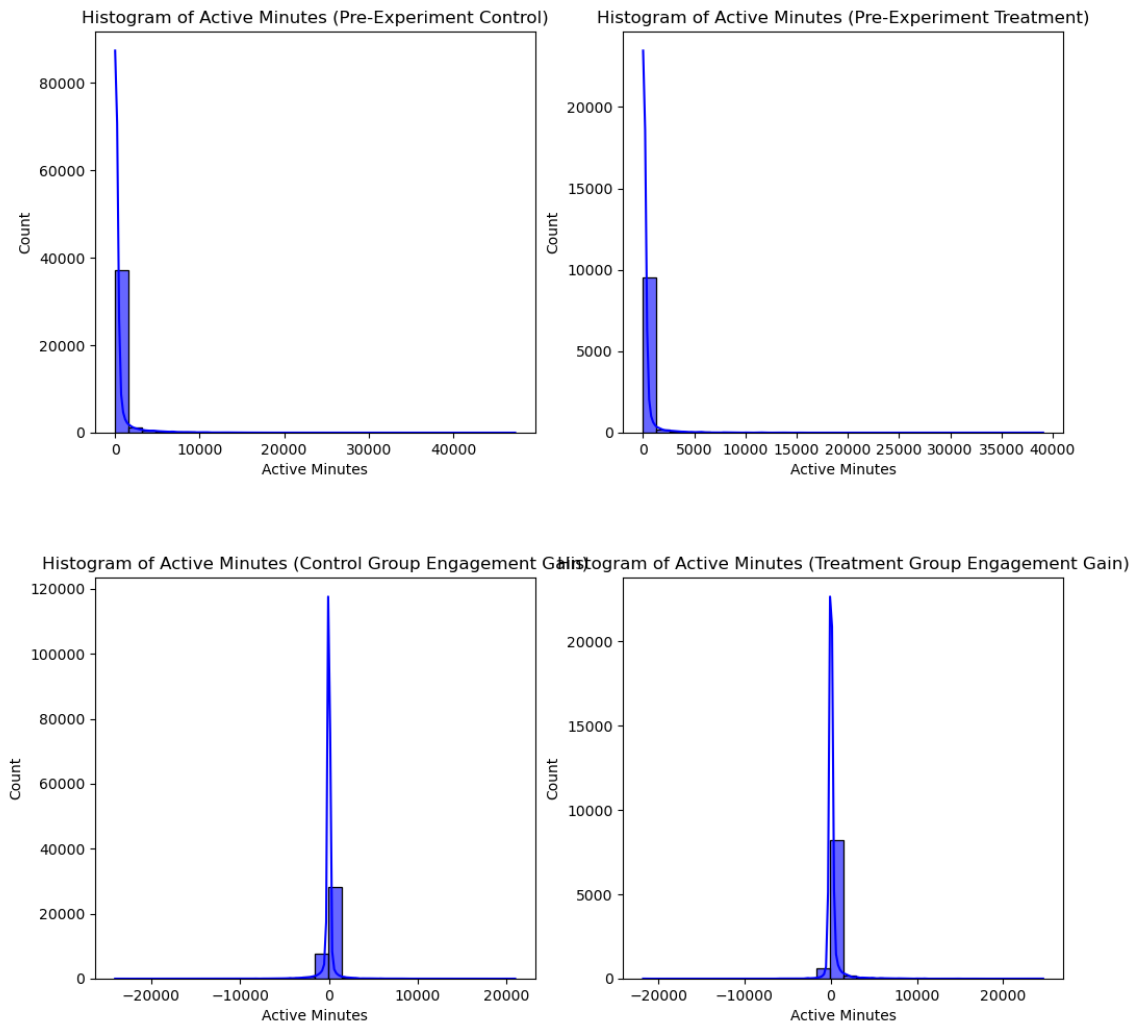
Engagement Gain Data:
  uid  pre_experiment_mins  post_experiment_mins  variant_number  engagement_gain
0    0                70.0                43.0            0            -27.0
1    1             19158.0             15205.0            0           -3953.0
2    2                37.0                17.0            0            -20.0
3    3             108.0                77.0            0            -31.0
4    4                66.0                39.0            0            -27.0

Summary Statistics for Engagement Gain:
variant_number  count      mean      std      min  25%  50%  75%   max
0             37313.0 -47.295447  968.271500 -24053.0 -47.0 -6.0  22.0  20942.0
1              9165.0  164.654119 1020.378387 -21776.0 -13.0 12.0  82.0  24636.0

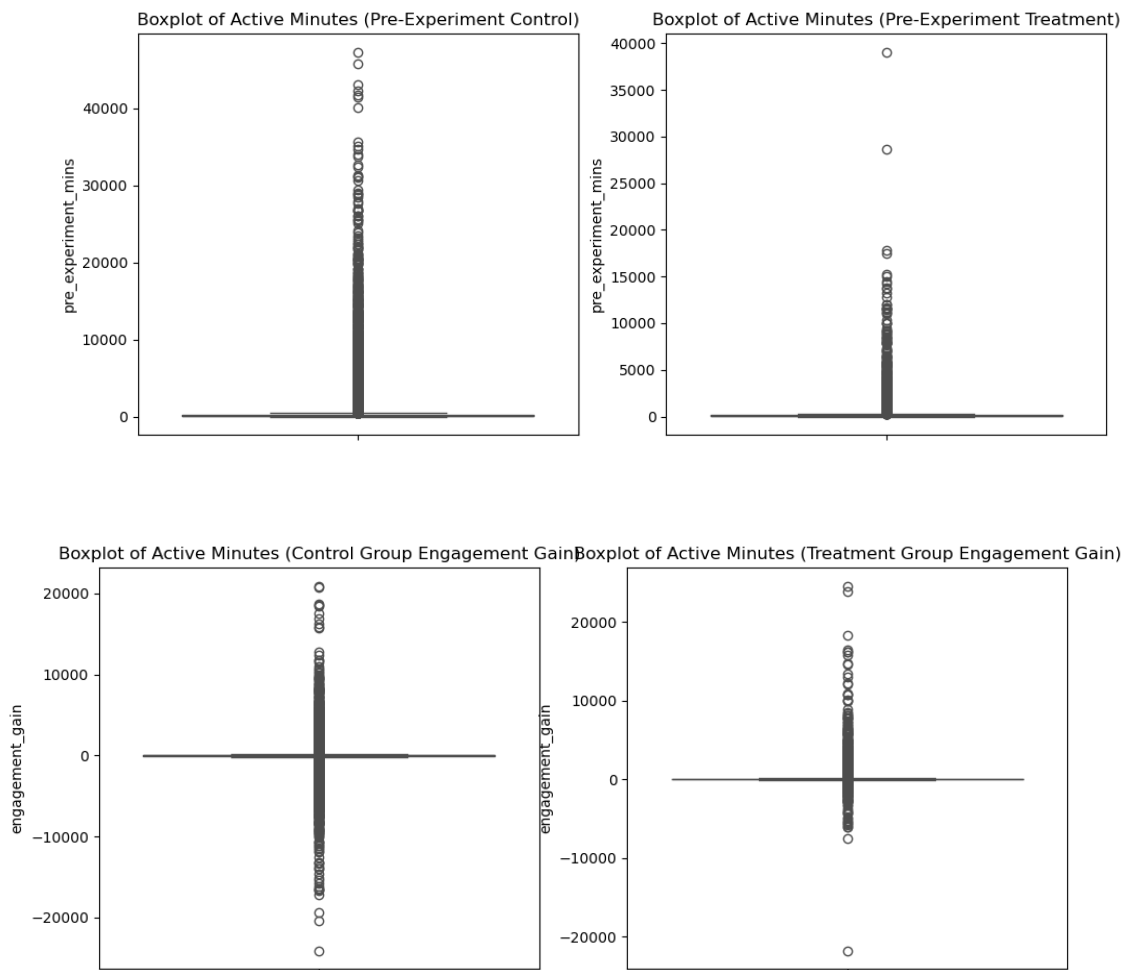
Mann-Whitney U-Test Result (Engagement Gain): MannwhitneyuResult(statistic=np.float64(125213006.5), pvalue=np.float64(0.0))

```

- Plotted histograms and boxplots to see if one group was using the platform more than the other before the update.







### 3. Are there any new conclusion?

- Before the update, the treatment group was using the platform less than the control group. This means the two groups were not equal from the start.
- After the update, the treatment group's engagement increased a lot (+164.65 minutes), while the control group's engagement dropped slightly (-47.3 minutes).
- The p-value is 0.0, so the difference between the groups is real and not due to random chance.
- This shows that the update helped increase engagement, but since the treatment group started with lower engagement, part of the increase could be due to a natural shift rather than purely because of the update.

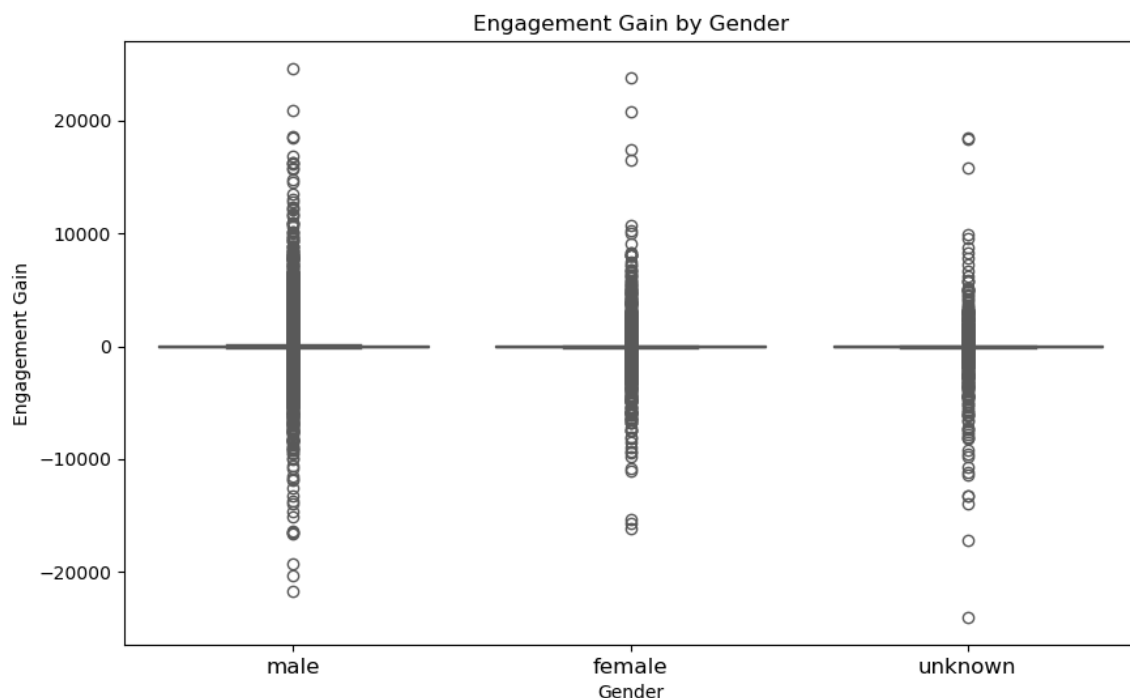
## Part 6: Exploring other conclusions

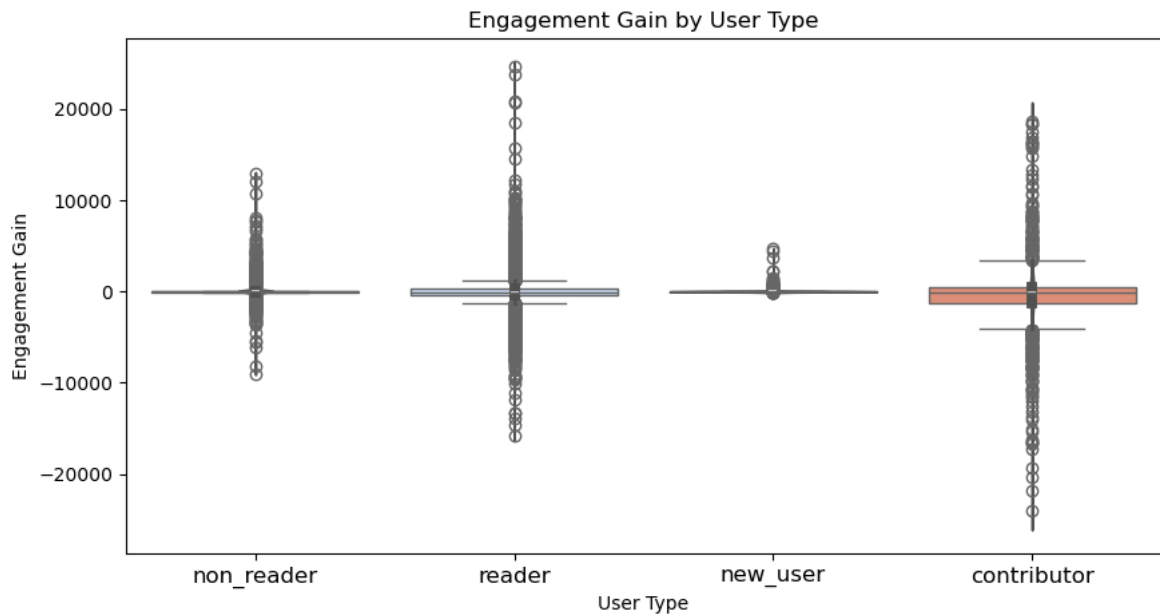
- Analyzed how engagement gain differs by gender and user type to see if the platform update affected some groups more than others.
- Merged user attributes (t4\_user\_attributes.csv) with engagement data to check differences by gender and user type and then calculated mean, median, and standard deviation for engagement gain in each group. Also created boxplots for visualization and performed a Mann-Whitney U-Test to check if male and female engagement changes were statistically different.

```
Engagement statistics by gender:
      mean  median      std
gender
female  -7.236927  -2.0  827.745260
male     0.270872  -3.0 1063.255580
unknown -23.419151  -3.0  938.834312

Engagement statistics by user type:
      mean  median      std
user_type
contributor -396.161850 -126.5 4185.257823
new_user     29.359974   5.0  167.901694
non_reader   10.769642  -4.0  299.199722
reader      -38.392448 -36.0 1714.084149

Mann-Whitney U-Test Result (Male vs. Female Engagement Gain): 0.06669190716448434
```





#### Gender Analysis:

- Males had a small engagement gain (+0.27 min), but females (-7.23 min) and unknown users (-23.41 min) experienced an engagement decline.
- The p-value (0.0667) shows no significant difference between male and female engagement.
- Boxplot shows similar distribution, meaning the update didn't impact one gender more than the other.

#### User Type Analysis:

- New users gained the most engagement (+29.36 minutes), while contributors dropped the most (-396.16 minutes).
- Readers (-38.39) and non-readers (+10.76) had small changes.
- Boxplot reveals high variation in contributors' engagement, suggesting some became highly active, while others lost interest.

#### Conclusion:

The update was most beneficial for new users but may have reduced engagement for existing contributors. Gender didn't play a major role in engagement changes.

## Part 7: Summarize Your Results

### Part 1: Understanding the Data

We explored the datasets to understand what each file contains. The files track user engagement before and after the experiment, assign users to groups (control or treatment), and provide user attributes. This helped us prepare for analysis.

## **Part 2: Merging the Data**

We merged post-experiment user activity (t1\_user\_active\_min.csv) with user assignments (t2\_user\_variant.csv) so we could compare engagement between the control and treatment groups.

## **Part 3: Initial Analysis**

We tested if the platform update increased engagement. The treatment group had significantly higher engagement, with a p-value of 0.0. However, we found outliers with unrealistic active minutes, which could affect the results.

## **Part 4: Removing Outliers**

We removed users with more than 1,440 active minutes per day. After cleaning the data, the treatment group still had higher engagement, confirming the update had a real effect.

## **Part 5: Checking Pre-Experiment Engagement**

We analyzed t3\_user\_active\_min\_pre.csv (pre-experiment engagement) to check if the two groups were equal before the update. Before the update, the treatment group had lower engagement than the control group. This means part of the increase in their engagement might be due to them naturally catching up, rather than entirely due to the update.

## **Part 6: Exploring Other Insights**

Here we analyzed how engagement gain differs by gender and user type with the help of user attributes (t4\_user\_attributes.csv). We found that the update was most beneficial for new users but may have reduced engagement for existing contributors. Gender didn't play a major role in engagement changes.

## **Final Conclusion:**

The new platform update significantly increased user engagement, as seen from our tests. But we also noticed that the treatment group was already using the platform less before the update. This means some of the increase in engagement may be influenced by their initially lower usage, rather than solely by the update. We also found that different types of users reacted differently. New users had the biggest gain, while contributors saw the biggest drop. Gender didn't seem to make a difference in engagement changes.