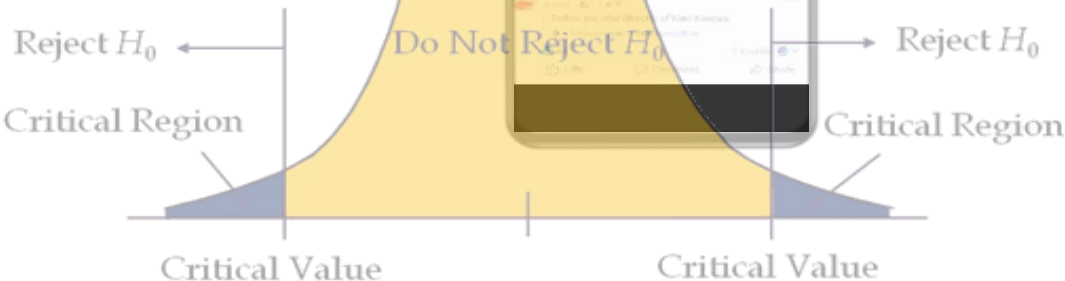


Analyzing the Impact of Facebook Group Treading Structure on Engagement: Was It Significant?

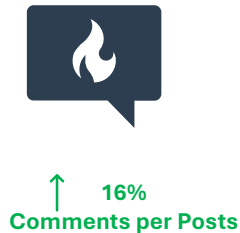
- Data Simulation
- Hypothesis testing
- Interpretation



Data Analytics Case:

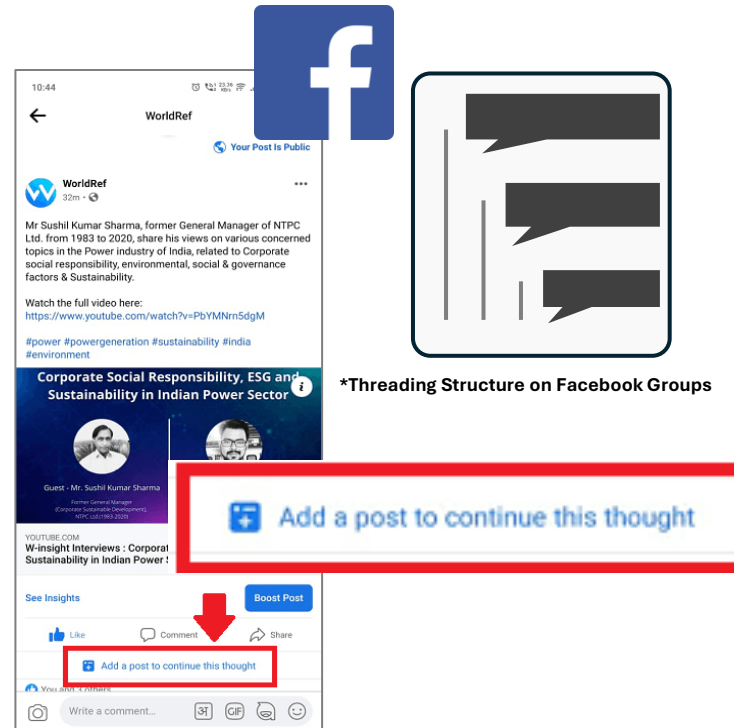
Let's say we work on Facebook Groups, and the Project Manager decided to add threading structures to comments, similar to other social media platforms like X or Reddit.

Observations:



After the change we observed that comments per posts increased by +16% but posts per user went down by -5%.

Why would that be?



Data Analytics Case:

Let's say we work on Facebook Groups, and the Project Manager decided to add threading structures to comments, similar to other social media platforms like X or Reddit.



We observe that comments per posts increased by 16% but posts per user went down by 5%. **Why would that be?**

a) Threading increases the loading time for the page, discouraging users from making new posts.

b) Threading disrupts the user interface, making it less appealing for users to create posts.

c) Threading structures discussions and encourages more comments within the same post, thereby reducing the need for new posts.

d) Threading makes it harder for users to post comments, leading to a decrease in posts.

Data Analytics Case:

Let's say we work on Facebook Groups, and the Project Manager decided to add threading structures to comments, similar to other social media platforms like X or Reddit.



↑+16%

Comments per Posts



↓-5%

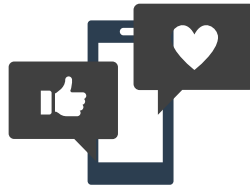
Posts per User

We observe that comments per posts increased by 16% but posts per user went down by 5%. **Why would that be?**

c) Threading structures discussions and encourages more comments within the same post, thereby reducing the need for new posts.

Logically, it makes sense that structures like those in X or Reddit encourage users to comment on posts.

Let's say our main goal is to improve the engagement rate in Facebook Groups



Did we achieve significant improvement towards the goal?

Simulating actions in an interdependent system on Facebook Groups

Since there is no data available for this specific business question, we can simulate a set of Facebook Group variables, establish interdependencies between them to generate realistic data, and conduct hypothesis testing

This model simulates engagement (**posts, comments, and reactions**) for 1,000 fictitious Facebook groups. It incorporates group type classification, probabilistic user behavior, and statistical distributions to estimate realistic engagement patterns

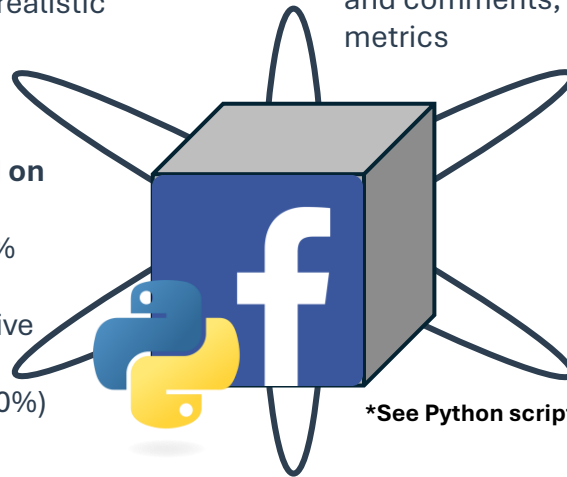
We establish an interdependent ecosystem where the group type (A, B, or C) and member count influence posts. More posts increase the likelihood of comments, and reactions depend on members, posts, and comments, simulating realistic engagement metrics

Each group is assigned a type based on empirical probabilities:

Type A (Hot Groups): Highly active (5% population)

Type B (Mild Groups): Moderately active (15%)

Type C (Cold Groups): Low activity (80%)




Finally, we adjust the model by **reducing post probability by 5%** and **increasing comment probability by 10%**. We then rerun the script to generate a new dataset for hypothesis testing.

[*See Python script here](#)

Now that we have two datasets (before and after), the next step is to establish a hypothesis to test whether the changes in post and comment probabilities significantly impacted engagement metrics.

Hypothesis Testing:

Let's say our main goal is to improve the engagement rate in Facebook Groups


+16%
Comments per
Posts


-5%
Posts per User

**Before threading layout in
Facebook Groups:**

Total Engagement: **2.09%**

**After introducing the new
layout:**

Total Engagement: **2.35%**↑

Yes, we can see an improvement in the total engagement but...

Did we achieve significant improvement towards the goal?

Null Hypothesis (H_0):

No significant difference in engagement between Model 1 and Model 2

Alternative Hypothesis (H_a):

There is a significant difference in engagement between Model 1 and Model 2

Hypothesis Testing:

Null Hypothesis (H_0):

No significant difference in engagement between Model 1 and Model 2

Alternative Hypothesis (H_a):

There is a significant difference in engagement between Model 1 and Model 2

We used an independent two-sample t-test because:

We are comparing the means of two independent samples: engagement percentages for Model 1 and Model 2

RULE:

- If $|t| > t_{\text{critical}}$, reject the null hypothesis
- If $|t| \leq t_{\text{critical}}$, fail to reject null hypothesis

For our case, the t-critical value for a two-tailed test with $\alpha=0.05$ and $df=1998$, based on the t-table, **t-critical is 1.960**.



Python $|t|$ test:

```
t_stat =  
scipy.stats.ttest_ind(engagement_1,  
engagement_2, equal_var=False)  
return  
t_stat  
T-statistic: -2.1115 or ABS =2.1115
```

RESULTS

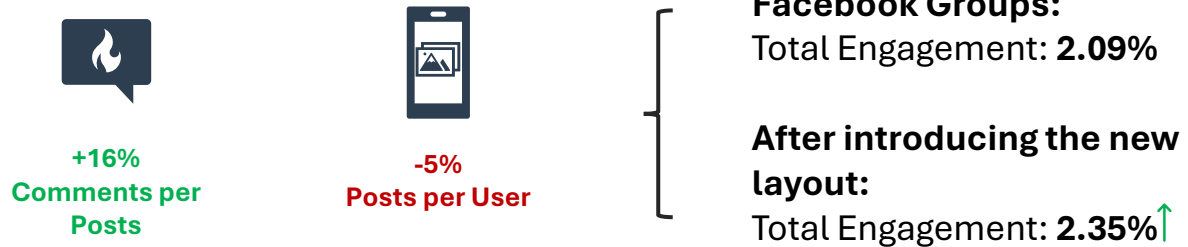
2.1115 ($|t|$) > 1.960 (t critical)
We reject the null hypothesis

Conclusion:

After conducting the test, we **reject the null hypothesis**, indicating a **statistically significant difference** in the **engagement percentage** between **Model 1 and Model 2**.

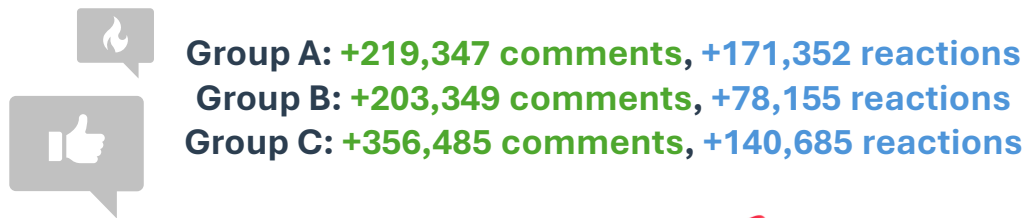
Business Perspective:

We now know for fact that the engagement was improved by our actions and not by just random fluctuation.



But from a business perspective, a small improvement of **only 0.26%** may not seem significant at **first glance**. However, we must remember that **Facebook is a massive digital platform**, where even small percentage changes can lead to **huge impacts**.

Based on the simulator numbers we achieved:



Not bad! 🚀