Marketing A/B Testing

March 2025

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DATA ANALYTICS

Overview

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Business Context

Business context

A company is running an A/B test to optimize their marketing campaign.

Experiment setup

- A **Control Group:** Sees a Public Service Announcement (PSA) or nothing.
- B **Experimental Group:** Sees ads.

Key questions

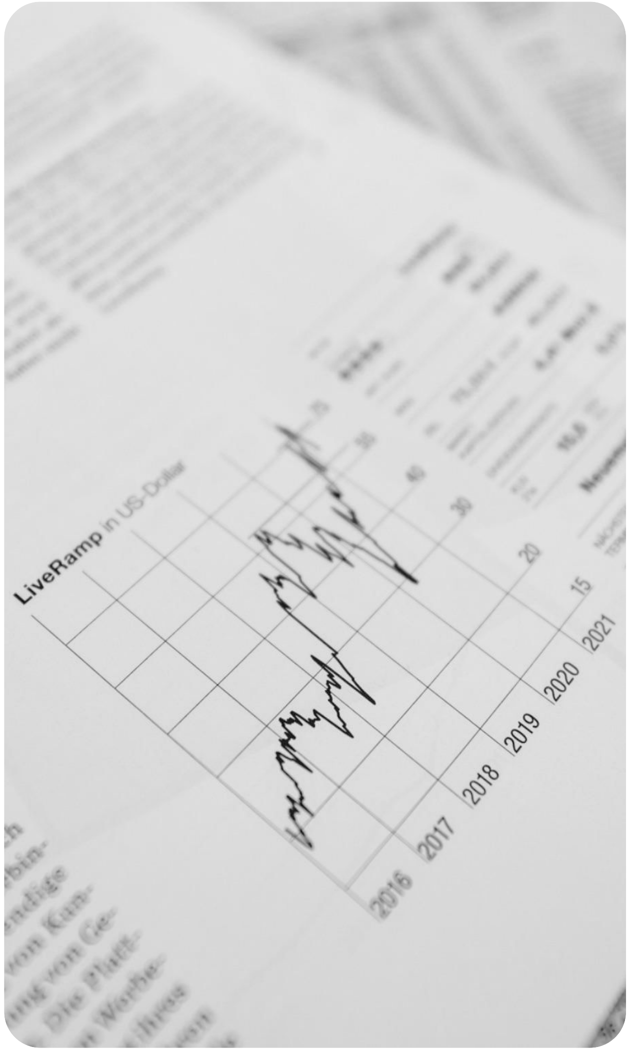
- Was the campaign successful?
- How much of the success is due to the ads?

Objectives

- Analyze group differences.
- Determine ad effectiveness.
- Assess statistical significance.

BACK

Executive Summary



Executive summary

Experiment overview

- 🅰 **Control Group:** Sees a Public Service Announcement (PSA) or nothing.
- 🅱 **Experimental Group:** Exposed to ads.

Key findings

- ✅ <u>Campaign Success:</u> Ads lead to a statistically significant improvement in conversions.

- 📊 <u>Ad Effectiveness:</u>

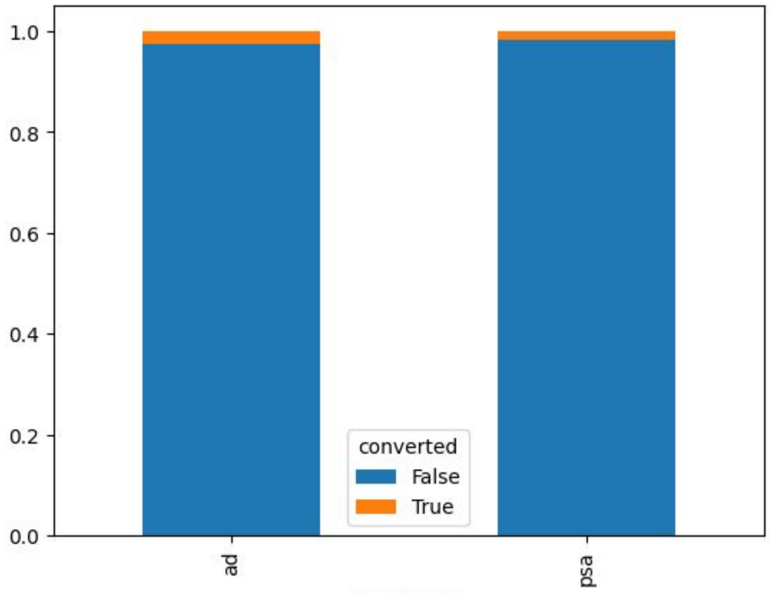
  - **Lift:** 0.75% difference between the control group and the ad group.

  - **Attribution Percentage:** **30% increase** in conversions (assuming ads are the only influencing factor).

  - **Odds ratio:** Odds of conversion are **44% higher** for those exposed to ads.

Conclusion

- ✅ **Ads significantly improve conversion rates**, with statistical analysis confirming a higher likelihood of success.



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Dataset Overview

Dataset overview [Link]

The dataset contains **user-level data** from an **A/B test** aimed at analyzing the impact of ads on customer conversions. It includes:

- **test group** (ad/PSA)
- **conversion status** (true/false)
- **ad exposure details** (total ads, peak day, and peak hour).

```
Total duplicate rows: 0
```

0
DUPLICATES

```
test group        2
converted         2
most ads day      7
most ads hour    24
```

4
CATEGORIES

```
Unnamed: 0      588101
```

588k
ROWS

```
Unnamed: 0
user id
```

2
DROPPED COLUMNS

	test group	converted	total ads	most ads day	most ads hour
0	ad	False	130	Monday	20
1	ad	False	93	Tuesday	22
2	ad	False	21	Tuesday	18
3	ad	False	355	Tuesday	10
4	ad	False	276	Friday	14

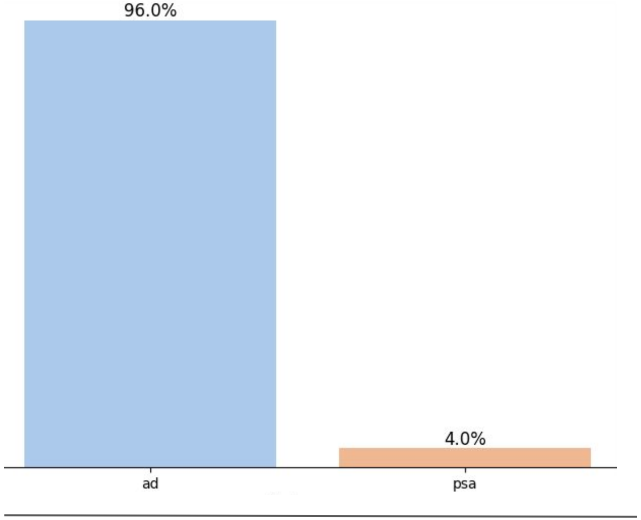
BACK

Descriptive Analysis

Descriptive analysis

Exposure

96% of the participants were **exposed** to the ads (vs. **4% control**)



Percent of dataset exposed to ads

BACK

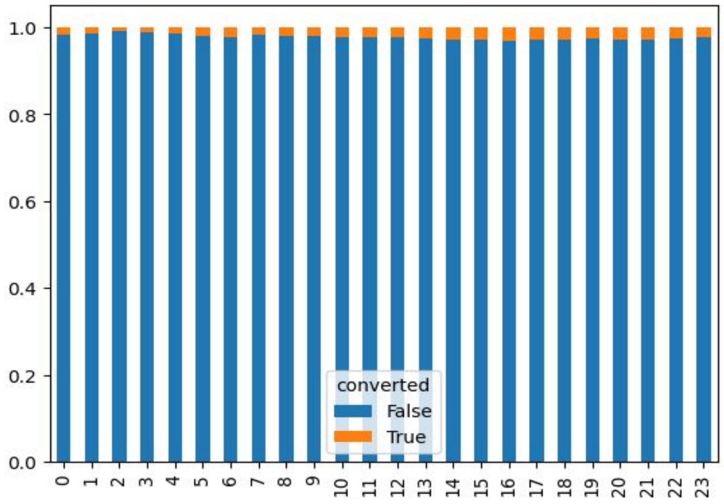
Descriptive analysis

Exposure

96% of the participants were **exposed** to the ads (vs. **4% control**)

Time

Adds between **10am** and **12pm** have the highest conversion



converted	False	True
most ads hour		
16	0.969228	0.030772
20	0.970197	0.029803
15	0.970347	0.029653
21	0.971077	0.028923
17	0.971790	0.028210
14	0.971937	0.028063
18	0.972620	0.027380
19	0.973280	0.026720
22	0.973895	0.026105
13	0.975323	0.024677
12	0.976172	0.023828
23	0.977338	0.022662
6	0.977756	0.022244
11	0.977884	0.022116
10	0.978479	0.021521

converted	False	True
most ads hour		
5	0.979085	0.020915
8	0.980484	0.019516
9	0.980809	0.019191
0	0.981575	0.018425
7	0.981889	0.018111
4	0.984765	0.015235
1	0.987089	0.012911
3	0.989548	0.010452
2	0.992687	0.007313

Time of ad vs. conversion rate

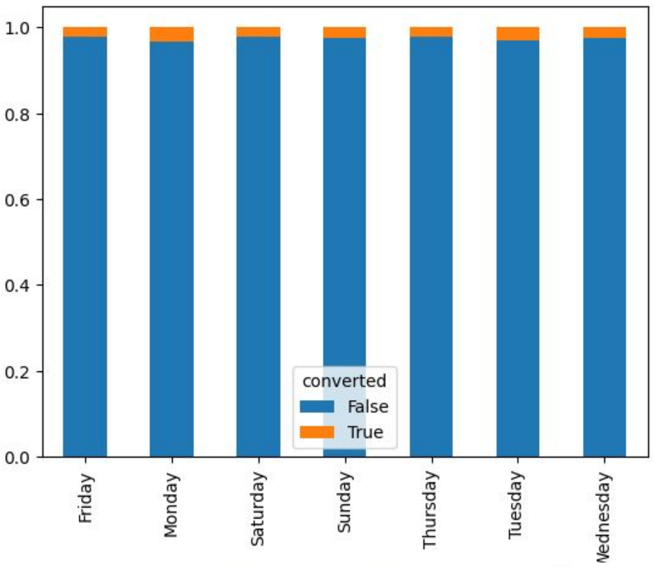
BACK

Descriptive analysis

Exposure
96% of the participants were **exposed** to the ads (vs. **4% control**)

Time
Adds between **10am** and **12pm** have the highest conversion

Day
Adds on **Monday** and **Tuesday** had the highest conversion rate



converted	False	True
most ads day		
Monday	0.967188	0.032812
Tuesday	0.970160	0.029840
Wednesday	0.975058	0.024942
Sunday	0.975524	0.024476
Friday	0.977788	0.022212
Thursday	0.978429	0.021571
Saturday	0.978949	0.021051

Day of ad vs. conversion rate

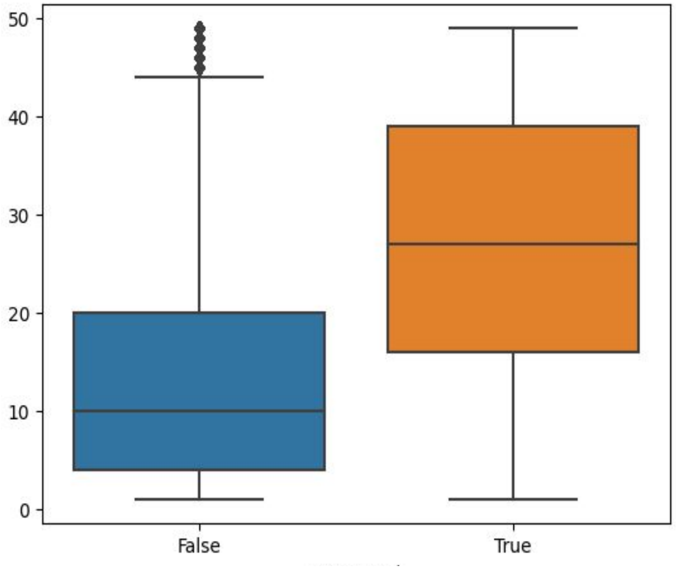
Descriptive analysis

Exposure
96% of the participants were **exposed** to the ads (vs. **4% control**)

Time
Adds between **10am** and **12pm** have the highest conversion

Day
Adds on **Monday** and **Tuesday** had the highest conversion rate

Amount of ads
The **more ads seen**, the **more likely** someone was **to convert**.

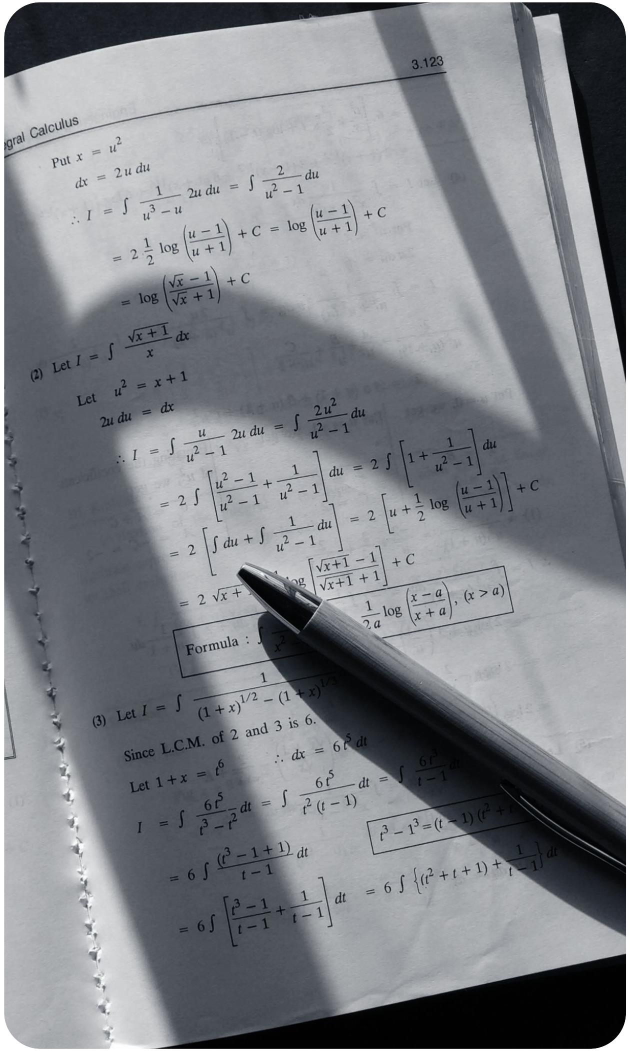


Amount of ads vs. conversion rate

BACK

Statistical Analysis

Q1 | Test group vs. conversion rates



Statistical analysis

Q1 | Methodology | Test group

Question

- Was the campaign successful?

Experiment setup

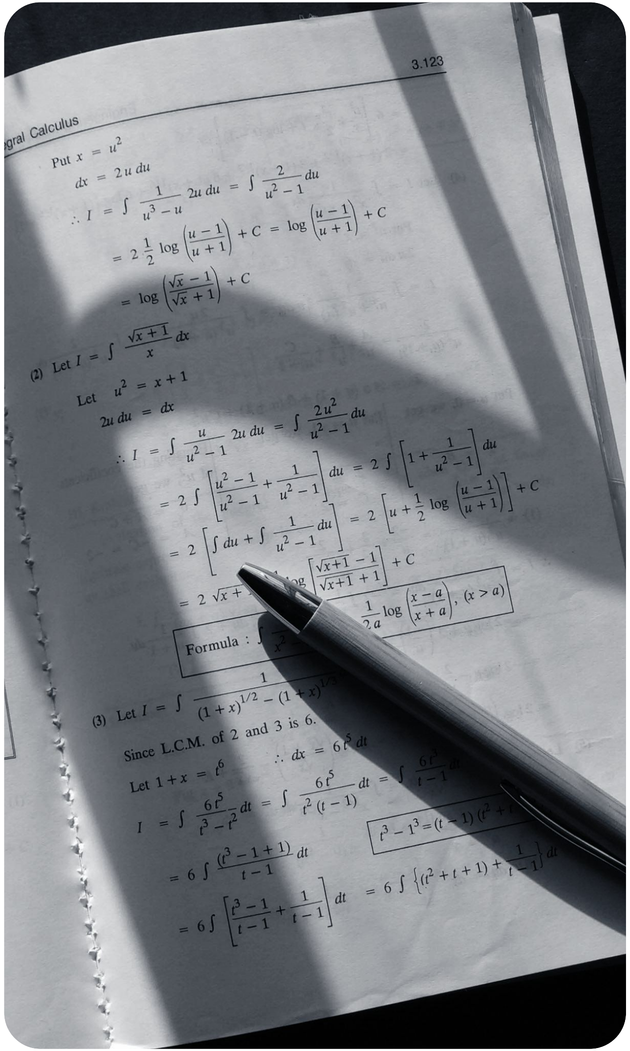
- Ⓐ **Control Group:** Sees a Public Service Announcement (PSA) or nothing.
- Ⓑ **Experimental Group:** Sees ads.

Hypothesis

- **Null Hypothesis (H0):** There is no difference in the conversion rates between the "ad" and "psa" groups.
- **Alternative Hypothesis (H1):** The "ad" group has a higher conversion rate than the "psa" group.

Objectives

- **Analyze group differences:** Conversion rates.
- **Assess statistical significance:** Chi-squared test.

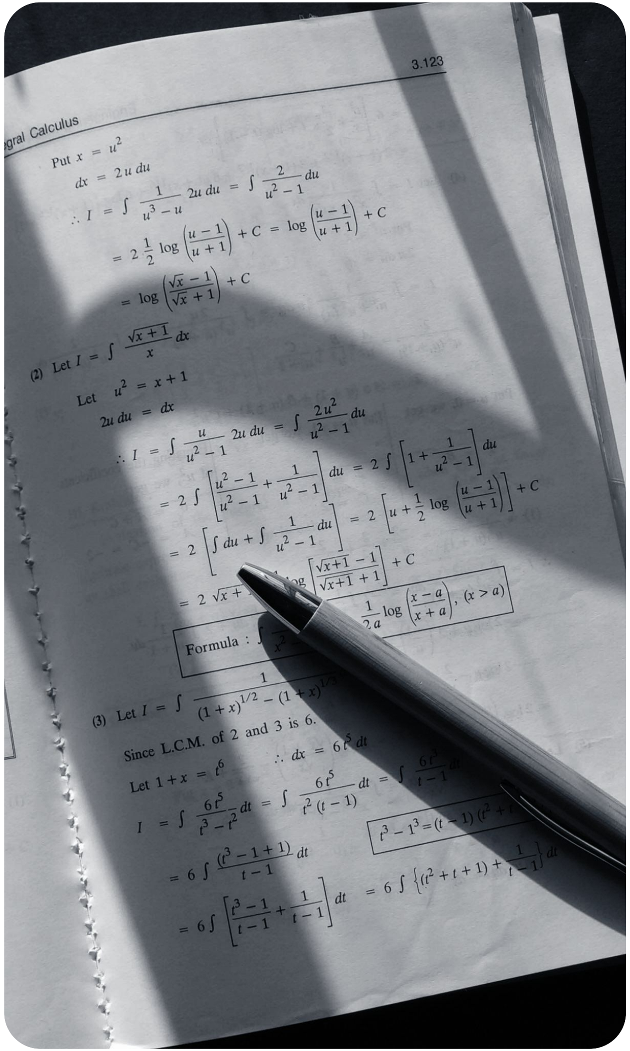


BACK

Statistical analysis

Q1 | Code | Test group

```python
# Separate the groups
ad_group = df[df['test group'] == 'ad']
psa_group = df[df['test group'] == 'psa']

# Calculate the conversion rate for each group
ad_conversion_rate = ad_group['converted'].mean()
psa_conversion_rate = psa_group['converted'].mean()

print(f"[CHI-SQUARE TEST FOR TEST GROUP VS. CONVERTED]")
print(f"\n\033[1mTEST GROUP\033[0m")
print(f"| • Conversion rate for 'ad' group: {ad_conversion_rate}")
print(f"| • Conversion rate for 'psa' group: {psa_conversion_rate}")

# Run a statistical test (Chi-square test)
## Create a contingency table of the form [ [ad_converted, ad_not_converted],
[psa_converted, psa_not_converted] ]
contingency_table = pd.crosstab(df['test group'], df['converted'])


## Perform Chi-square test
chi2_stat, p_value, dof, expected = stats.chi2_contingency(contingency_table)

print(f"| • Chi-square stat: {chi2_stat.round(2)}")
print(f"| • p-value (6 decimals): {p_value:.6f}")
print(f"| • P-value: {p_value:.20f}")
```



BACK

Statistical analysis

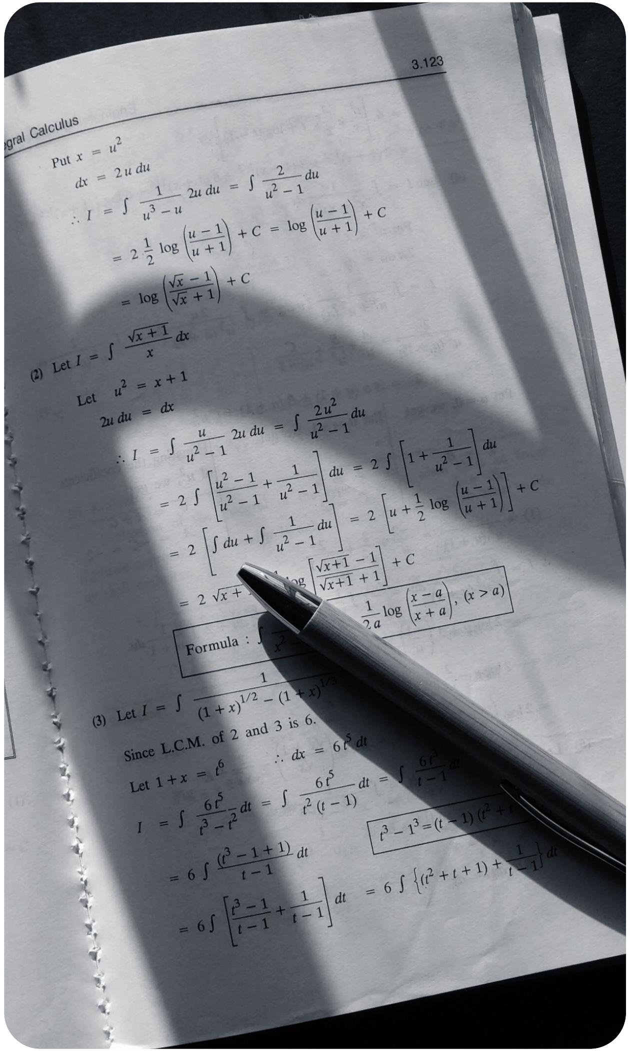
Q1 | Results | Test group

Test group vs. Converted

- **Conversion rate for 'ad' group:** 0.026
- **Conversion rate for 'psa' group:** 0.018
- **Chi-square stat:** 54
- **p-value (6 decimals):** 0.000000
- **p-value:** 0.000000000000019989623

Interpretation

- ✅ **Significant result:** Reject null hypothesis. This means that conversion rates differ between users who saw ads and those who saw PSAs, indicating that ads likely had an impact on conversions.
    - ❌ **Null Hypothesis (H_0):** Conversion rates do not differ between the test groups (ad vs. PSA).
    - ✅ **Alternative Hypothesis (H_1):** Conversion rates do differ between the test groups.



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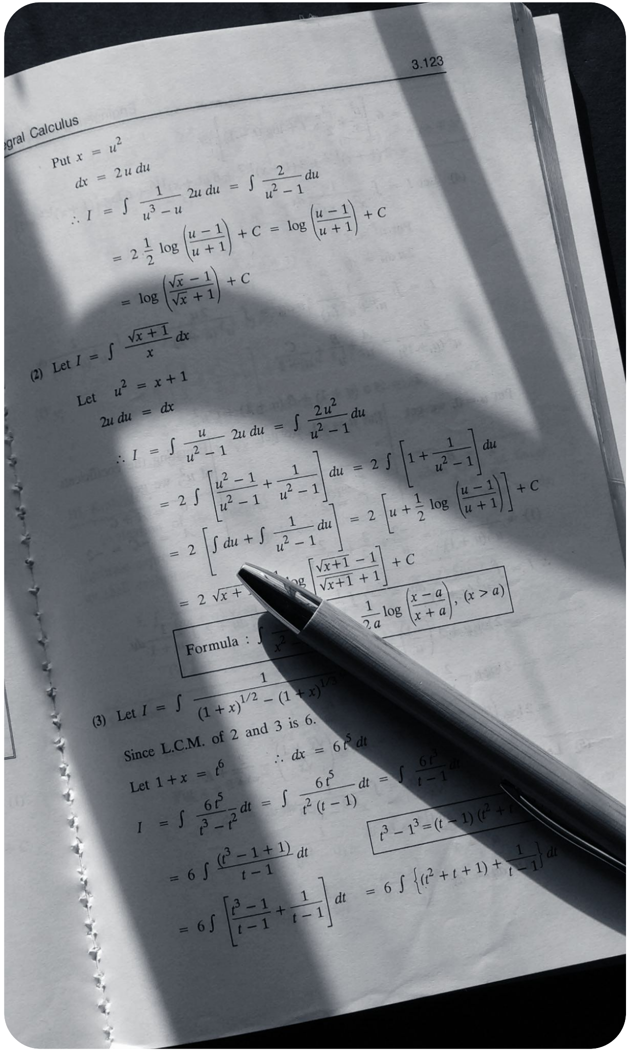
Statistical Analysis

Q1 | Ad day vs. conversion rates



Statistical analysis

Q1 | Methodology | Ad day

Question

- Does the day of the week where a user saw the most ads impact conversion rates?

Experiment setup

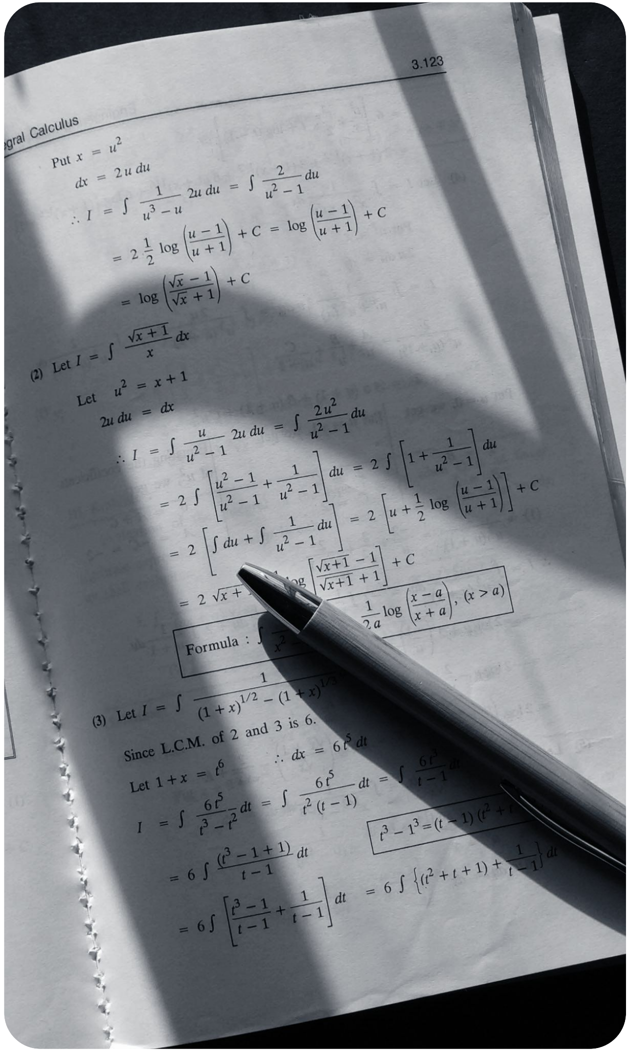
- Ⓐ **Control Group:** Sees a Public Service Announcement (PSA) or nothing.
- Ⓑ **Experimental Group:** Sees ads.

Hypothesis

- **Null Hypothesis (H_0):** Conversion rates do not differ across days.
- **Alternative Hypothesis (H_1):** Conversion rates do differ depending on the most ads day.

Objectives

- **Analyze group differences:** Conversion rates.
- **Assess statistical significance:** Chi-squared test.

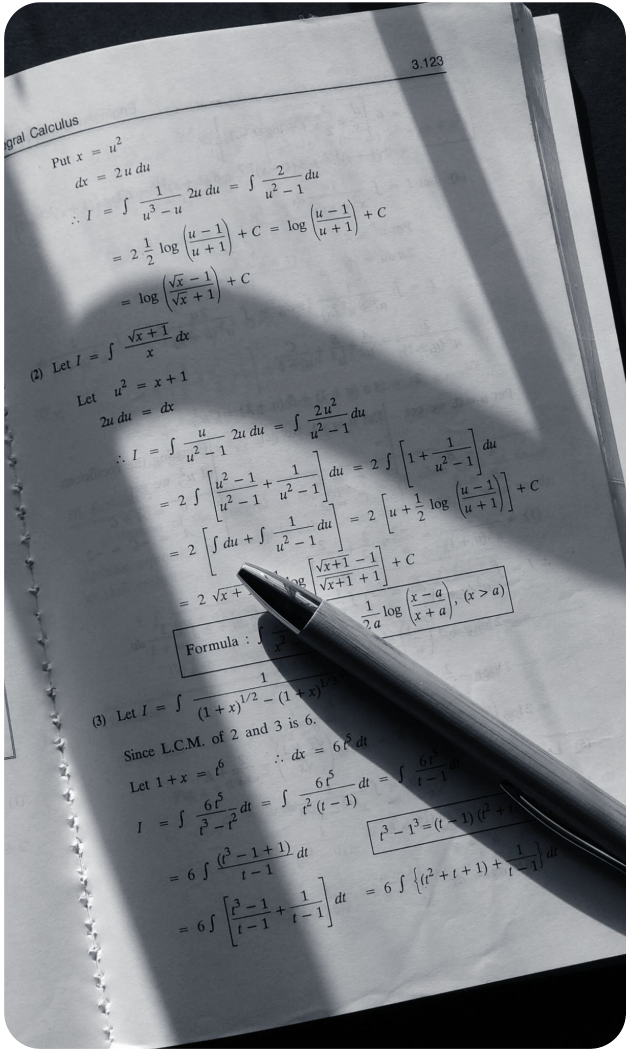


BACK

Statistical analysis

Q1 | Code | Ad day

```
# Variables
df_categorical_variables = df[["converted", "most ads day", "most ads hour"]]
alpha = 0.05

# Title
print("[CHI-SQUARE TEST FOR EACH {VARIABLE} VS. CONVERTED]")

# Loop for each variable
for variable in df_categorical_variables.columns:

    if variable != 'converted':

        # Create a contingency table (cross-tab)
        contingency_table =
        pd.crosstab(df_categorical_variables[variable],df_categorical_variables
        ["converted"])

        # Chi-squared test
        chi2,p, _, _ = chi2_contingency(contingency_table)

        # Results
        print(f"\n\033[1m{variable.upper()}\033[0m")
        print(f"| • Chi-square value: {chi2.round(2)}")
        print(f"| • p-value (6 decimals): {p:.6f}")
        print(f"| • p-value: {p:.90f}")
```



BACK

Statistical analysis

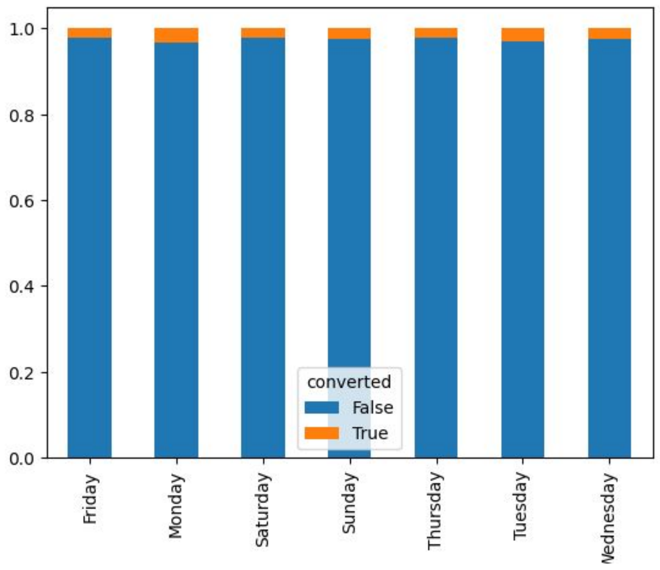
Q1 | Results | Ad day

Ad day vs. Converted

- **Chi-squared value:** 410
- **p-value (6 decimals):** 0.000000

Interpretation

- ✅ **Significant:** Reject the null hypothesis. This means that conversion rates vary depending on the most ads day
  - ❌ **Null Hypothesis (H_0):** Conversion rates do not differ across days.
  - ✅ **Alternative Hypothesis (H_1):** Conversion rates do differ depending on the most ads day.

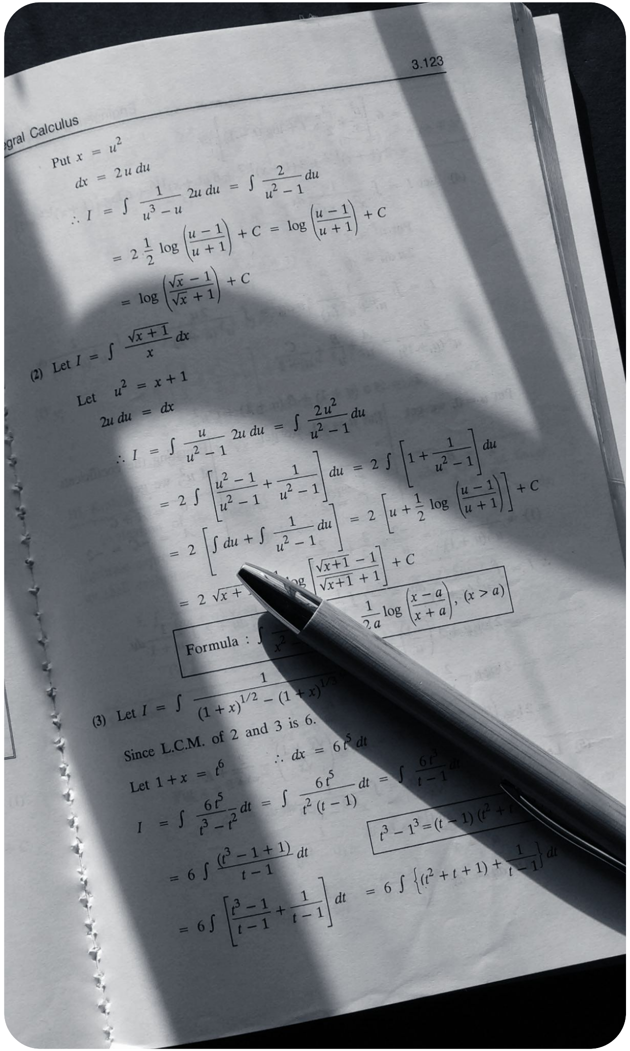


Day of ad vs. conversion rate

BACK

Statistical Analysis

Q1 | Ad hour vs. conversion rates



Statistical analysis

Q1 | Methodology | Ad hour

Question

- Does the hour where a user saw the most ads impact conversion rates?

Experiment setup

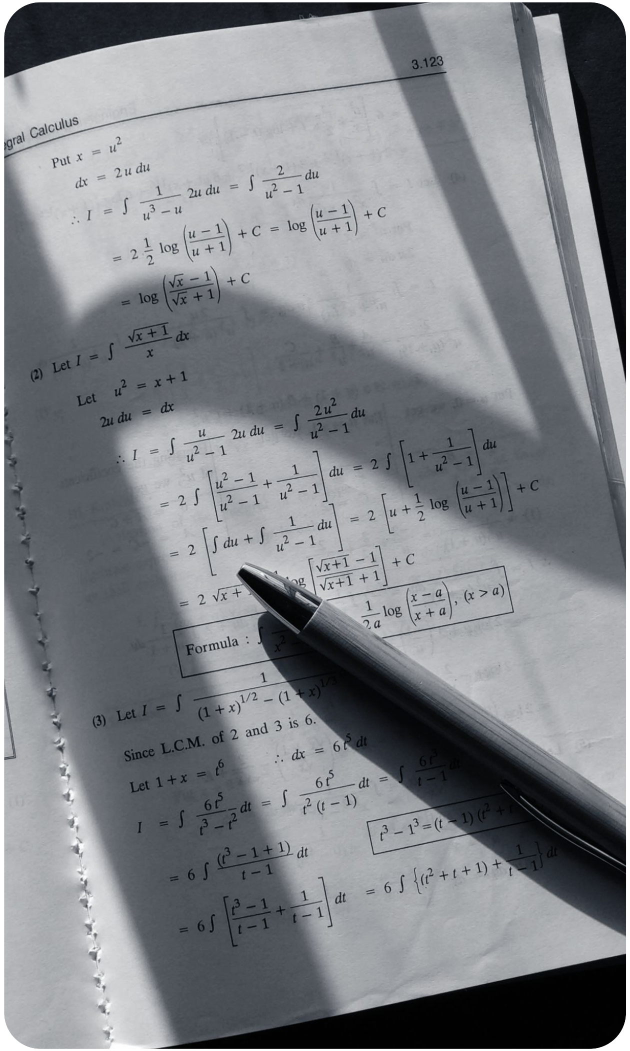
- Ⓐ **Control Group:** Sees a Public Service Announcement (PSA) or nothing.
- Ⓑ **Experimental Group:** Sees ads.

Hypothesis

- **Null Hypothesis (H_0):** Conversion rates do not depend on the hour of the most ads.
- **Alternative Hypothesis (H_1):** Conversion rates do depend on the most ads hour.

Objectives

- **Analyze group differences:** Conversion rates.
- **Assess statistical significance:** Chi-squared test.

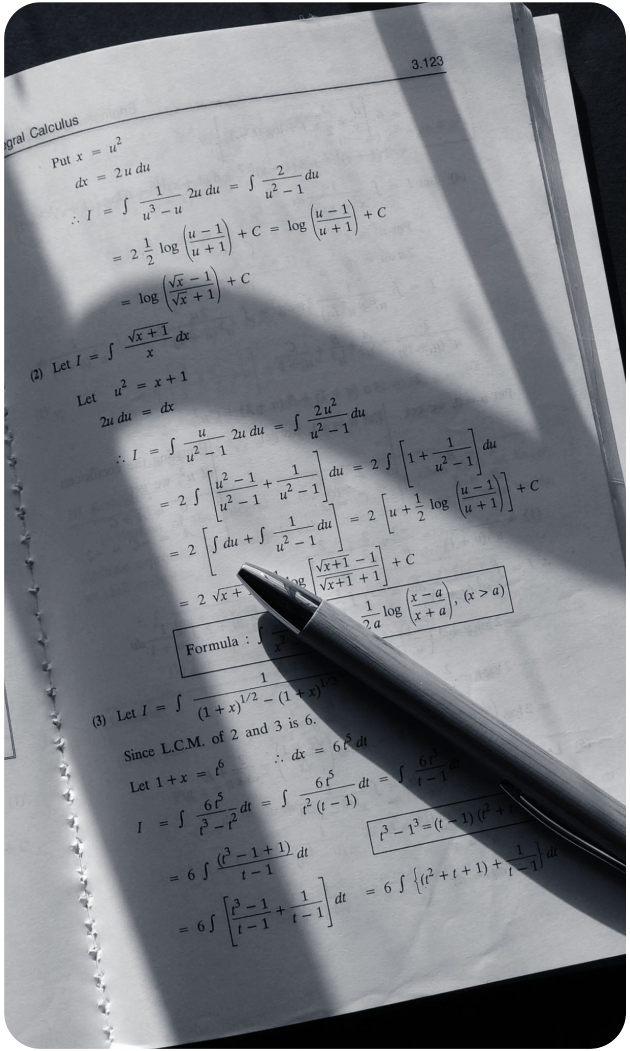


BACK

Statistical analysis

Q1 | Code | Ad hour

```
# Variables
df_categorical_variables = df[["converted", "most ads day", "most ads hour"]]
alpha = 0.05

# Title
print("[CHI-SQUARE TEST FOR EACH {VARIABLE} VS. CONVERTED]")

# Loop for each variable
for variable in df_categorical_variables.columns:

    if variable != 'converted':

        # Create a contingency table (cross-tab)
        contingency_table =
        pd.crosstab(df_categorical_variables[variable],df_categorical_variables
        ["converted"])

        # Chi-squared test
        chi2,p, _, _ = chi2_contingency(contingency_table)

        # Results
        print(f"\n\033[1m{variable.upper()}\033[0m")
        print(f"| • Chi-square value: {chi2.round(2)}")
        print(f"| • p-value (6 decimals): {p:.6f}")
        print(f"| • p-value: {p:.90f}")
```



BACK

Statistical analysis

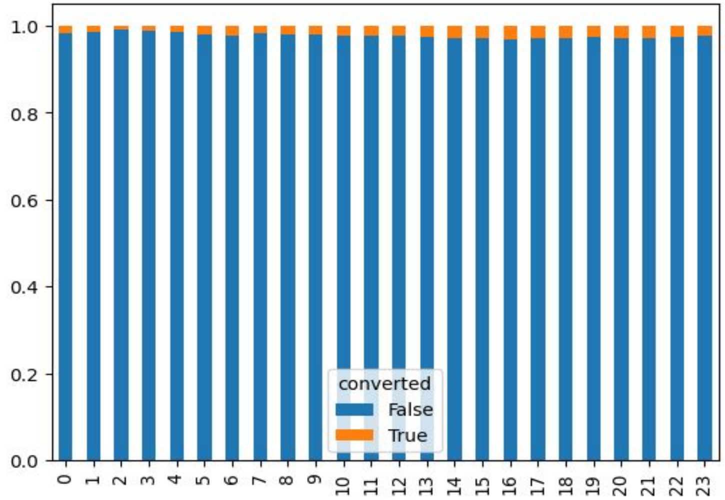
Q1 | Results | Ad hour

Most ads hour vs. Converted

- Chi-squared value: 431
- p-value (6 decimals): 0.000000

Interpretation

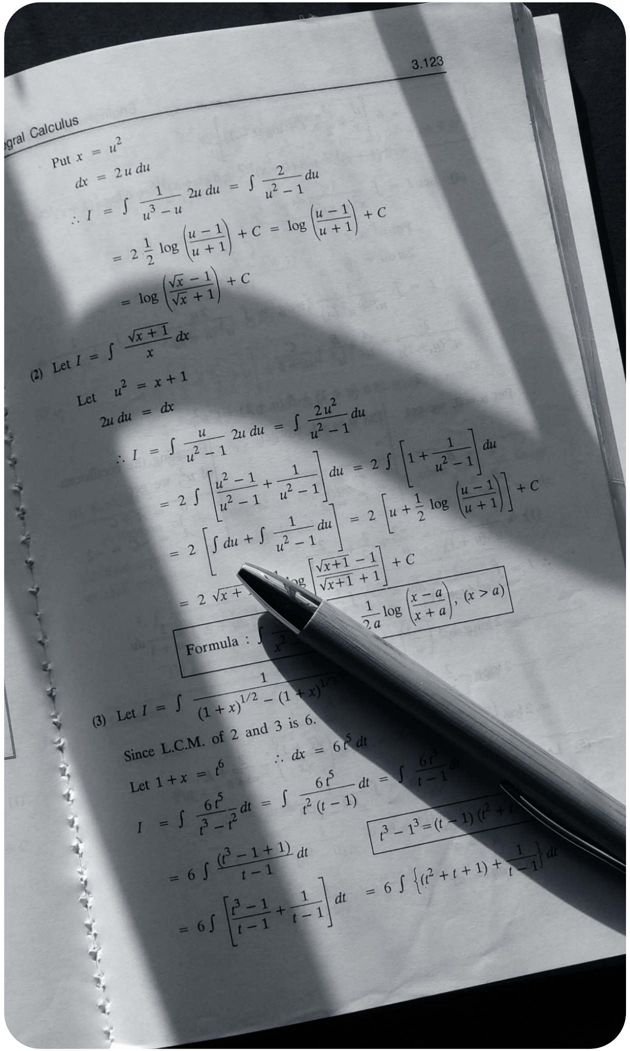
- ✅ **Significant:** Reject the null hypothesis. Means that conversion rates differ depending on the hour users see the most ads
  - ❌ Null Hypothesis (H_0): Conversion rates do not depend on the hour of the most ads.
  - ✅ Alternative Hypothesis (H_1): Conversion rates do depend on the most ads hour.



Time of ad vs. conversion rate

Statistical Analysis

Q1 | Total ads vs. conversion rates



Statistical analysis

Q1 | Methodology | Total ads

Question

- Was the campaign successful?

Experiment setup

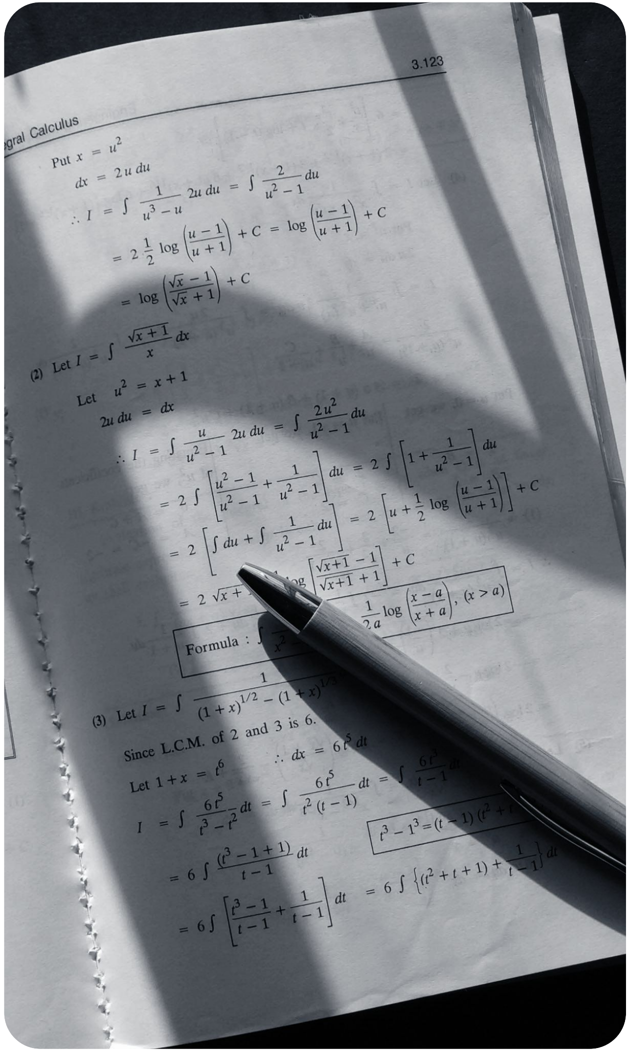
- Ⓐ **Control Group:** Sees a Public Service Announcement (PSA) or nothing.
- Ⓑ **Experimental Group:** Sees ads.

Hypothesis

- **Null Hypothesis (H0):** The amount of ads make no difference in the conversion rates between the "ad" and "psa" groups.
- **Alternative Hypothesis (H1):** The amount of ads makes a difference on the conversion rates between the “ad” and “psa” groups.

Objectives

- **Analyze group differences:** Total adds & conversion rates.
- **Assess statistical significance:** Mann-Whitney U test.

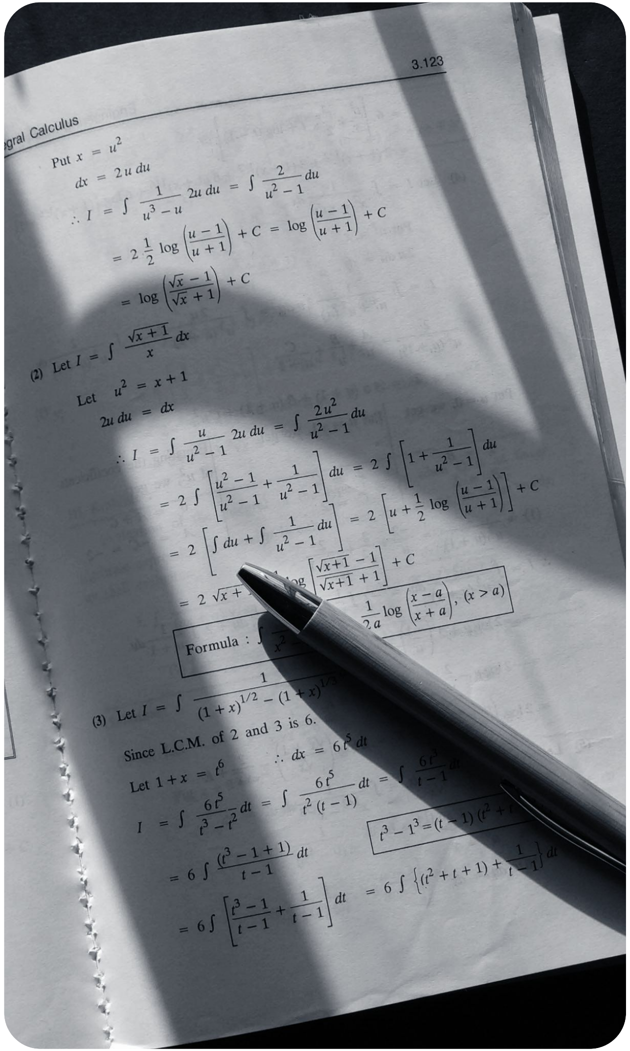


BACK

Statistical analysis

Q1 | Code | Total ads

```python
from scipy.stats import shapiro, levene, ttest_ind, mannwhitneyu
alpha = 0.05

# Check assumptions
print("[NORMALITY AND EQUALITY OF VARIANCES ASSUMPTIONS]")

## Normality Assumption
shapiro_stat_true, shapiro_p_value_true = shapiro(df[df['converted'] == True]["total ads"])
shapiro_stat_false, shapiro_p_value_false = shapiro(df[df['converted'] == False]["total ads"])

print(f"\n\033[1mShapiro-Wilk Test for Normality (True group)\033[0m")
print(f"| • p-value: {shapiro_p_value_true:.6f}")
print(f"\033[1mShapiro-Wilk Test for Normality (False group)\033[0m")
print(f"| • p-value: {shapiro_p_value_false:.6f}")

# Equality of variances assumption
levene_stat, levene_p_value = levene(df[df['converted']]["total ads"], df[~df['converted']]['total ads'])

print(f"\n\033[1mLevene's Test for Equality of Variances\033[0m")
print(f"| • p-value: {levene_p_value:.6f}")

# Perform statistical test
print("\n[STATISTICAL TEST SELECTION]")

if shapiro_p_value_true > alpha and shapiro_p_value_false > alpha and levene_p_value > alpha:
    # Assumptions met - use t-test for means
    t_stat, t_p_value = ttest_ind(df[df['converted']]['total ads'],df[~df['converted']]['total ads'])
    print(f"\n\033[1mIndependent Two-Sample t-test\033[0m")
    print(f"| • p-value: {t_p_value:.6f}")

else:
    # Assumptions not met - use Mann-Whitney U test for medians
    u_stat, u_p_value = mannwhitneyu(df[df['converted']]['total ads'],df[~df['converted']]['total ads'])
    print(f"\n\033[1mMann-Whitney U Test\033[0m")
    print(f"| • p-value: {u_p_value:.6f}")
```



BACK

Statistical analysis

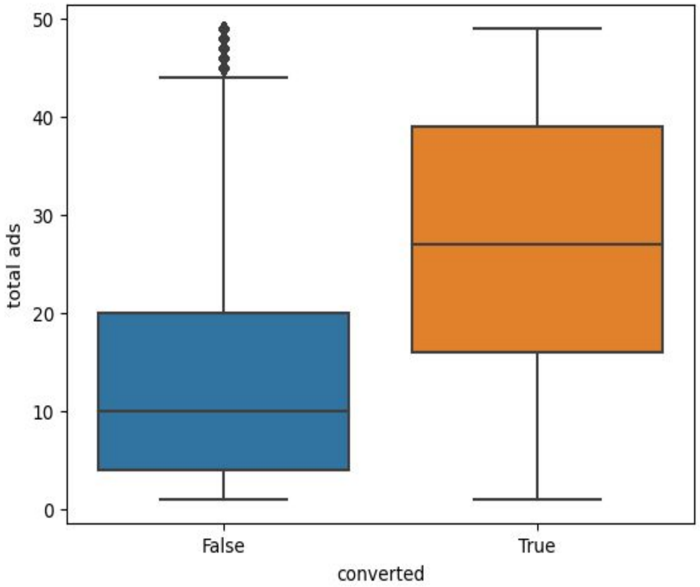
Q1 | Results | Total ads

Total ads vs. Converted

- Shapiro-Wilk Test for Normality (True group)
  - p-value: 0.000000
- Shapiro-Wilk Test for Normality (False group)
  - p-value: 0.000000
- Levene's Test for Equality of Variances
  - p-value: 0.000000
- Mann-Whitney U Test
  - p-value: 0.000000

Interpretation

- ✅ **Significant result:** The conversion rates between the 'True' and 'False' groups differ significantly based on the Mann-Whitney U test for medians.
  - ❌ Null Hypothesis (H_0): The amount of ads make no difference in the conversion rates between the "ad" and "psa" groups.
  - ✅ Alternative Hypothesis (H_1): The amount of ads makes a difference on the conversion rates between the “ad” and “psa” groups.



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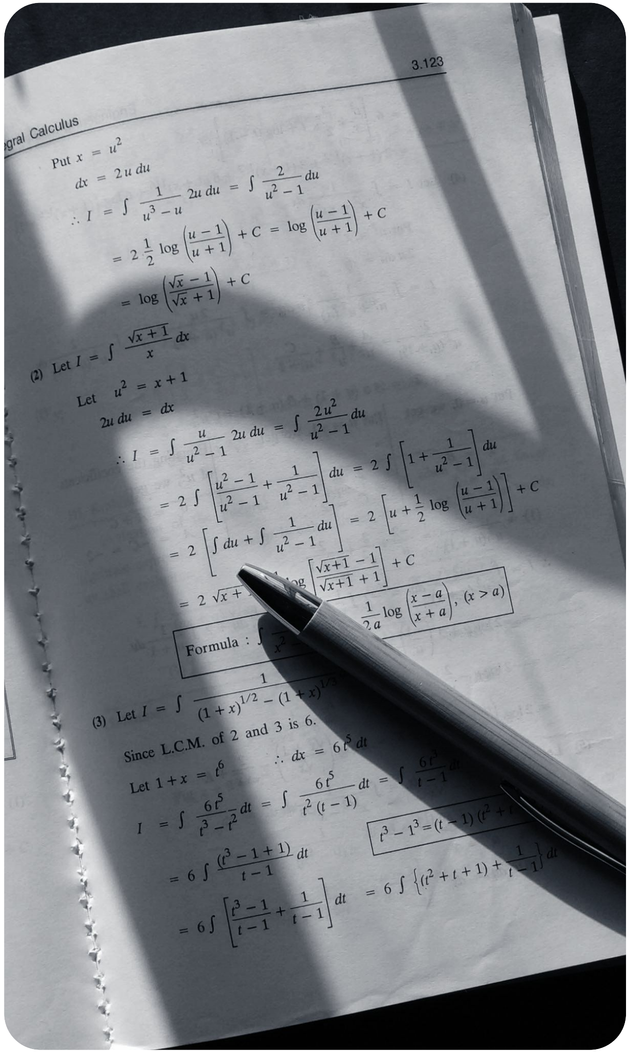
Statistical Analysis

Q2 | Attribution percentage: impact of ads on conversion rates



Statistical analysis

Q2 | Methodology | Attribution Percentage

Formula

$$Attributionpercentage = \left(\frac{ConversionRateDifference}{ControlGroupConversionRate}\right) \times 100$$

Steps

- **1. Measure lift:** Compute the difference in conversion rates between the ad group and psa group
  Example: *2.54% – 1.79% = 0.75%.*

- **2. Normalise:** Express lift as a proportion of the ad group's total conversions.
  Example: *0.75% / 1.79% = 0.419%*

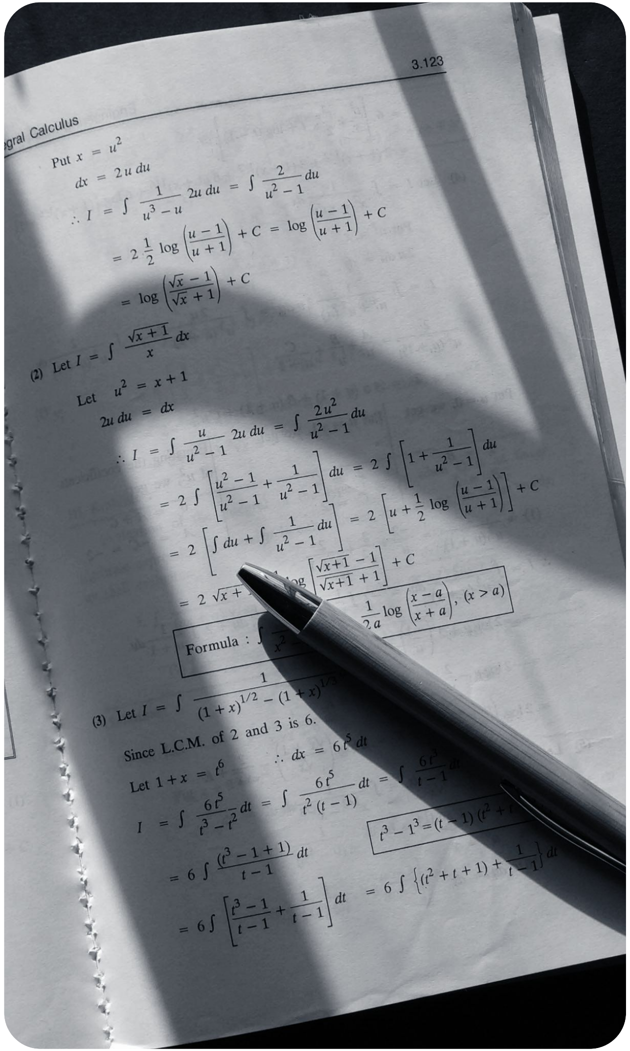
- **3. Convert to percentage:** Multiply by 100 to get the final attribution: 42%

Key insights

- This method estimates what proportion of the total conversions (or other outcomes) are attributable to the ad exposure.

Limitations

- Assumes all conversion rate differences are due to ads.
- Doesn't account for external factors like seasonality or organic trends.

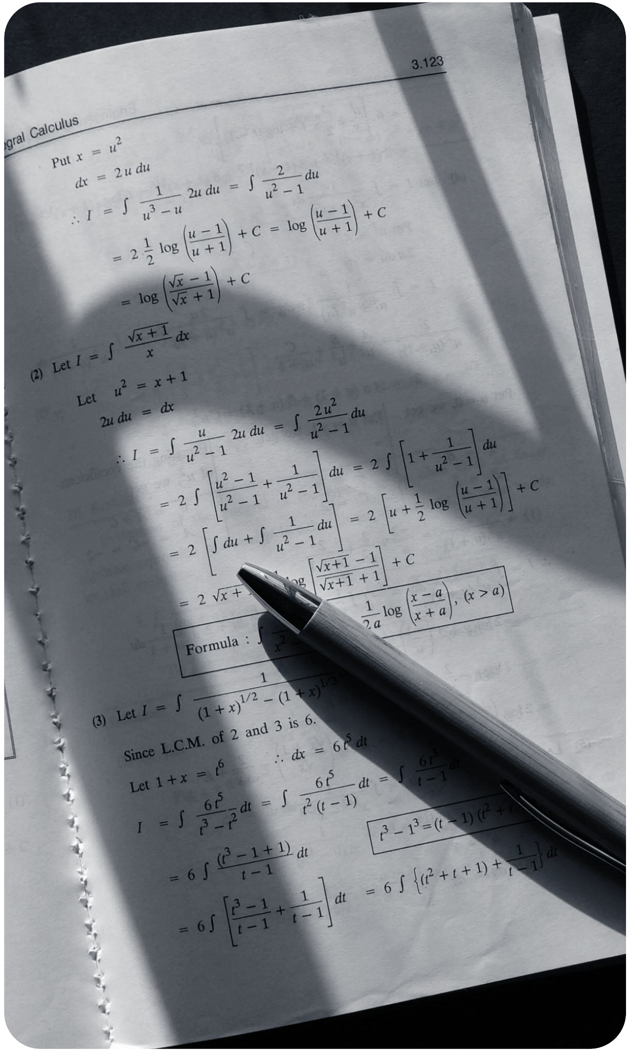


BACK

Statistical analysis

Q2 | Code | Attribution percentage

```
# Compare Conversion Rates Between Ad Group and PSA Group

# Calculate conversion rates for both 'ad' and 'psa' groups
ad_group_conversion_rate = df[df['test group'] == 'ad']['converted'].mean()
psa_group_conversion_rate = df[df['test group'] == 'psa']['converted'].mean()

# Display the conversion rates
print(f"Conversion rate for 'ad' group: {ad_group_conversion_rate:.10f} |
{ad_group_conversion_rate*100:.10f}% ")
print(f"Conversion rate for 'psa' group: {psa_group_conversion_rate:.10f} |
{psa_group_conversion_rate*100:.10f}% ")

# Calculate the difference in conversion rates
conversion_rate_diff = ad_group_conversion_rate - psa_group_conversion_rate
print(f"Difference in conversion rates (ad - psa): {conversion_rate_diff:.10f} |
{conversion_rate_diff*100:.10f}%")

# Estimate Attribution to Ads (Simple Difference)
## Calculate the attribution percentage
attribution_percentage = (conversion_rate_diff / ad_group_conversion_rate) * 100

## Display the attribution percentage
print(f"\nEstimated Attribution to Ads: {attribution_percentage:.2f}%")
```



BACK

Statistical analysis

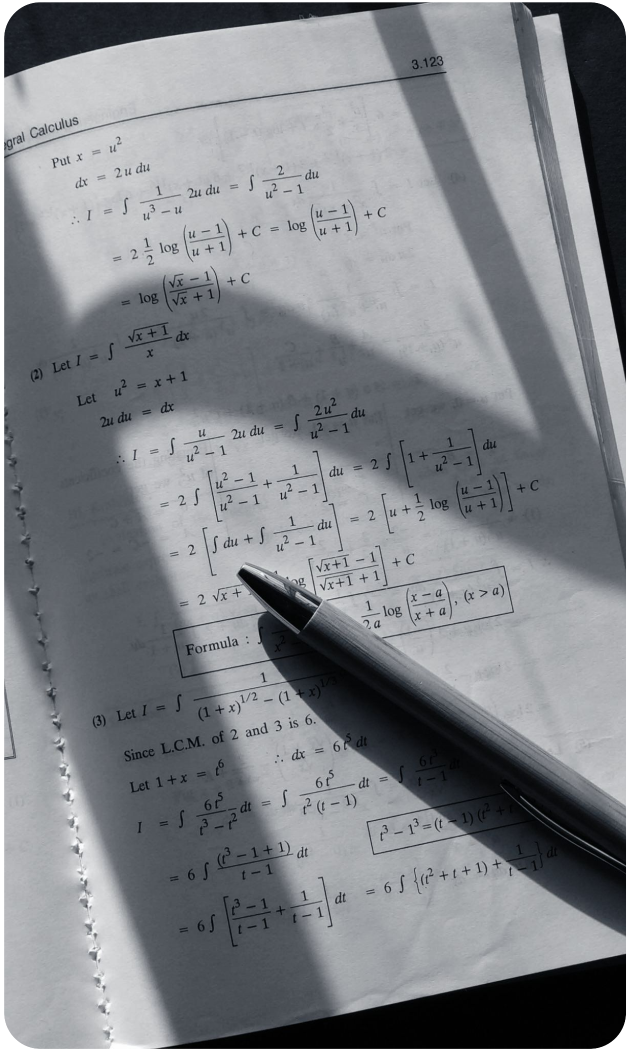
Q2 | Results | Attribution percentage

Impact

- Conversion rate for 'ad' group: 2.54%
- Conversion rate for 'psa' group: 1.79%
- Lift: 0.75%
- Estimated Attribution to Ads: 42%

Interpretation

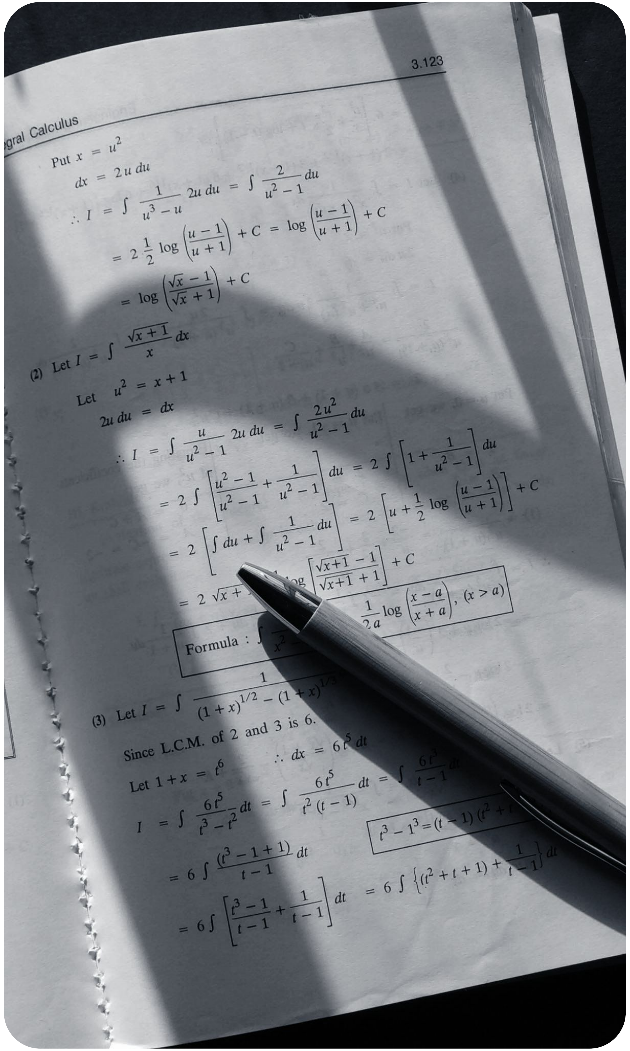
- The simple difference shows a 30% increase in conversion.
- However, this assumes that the only factor influencing conversions is the ads themselves.



BACK

Statistical Analysis

Q2 | Odds ratio: impact of ads on conversion rates



Statistical analysis

Q2 | Methodology | Odds ratio

Formula

Odds Ratio = $e^{(\beta_1)}$

Where:

- β_1 = Coefficient for ad exposure (0.3661)
- e = Euler's number (approx. 2.718)

Steps

- 1. Calculate the Odds Ratio:
    - Odds Ratio = $e^{(\beta_1)}$
      Example: *$e^{0.3661} = 1.442$*
- 2. Convert to Percentage Lift:
    - Percentage Lift = (Odds Ratio − 1) × 100
      Example: *(1.442 − 1) × 100 = 44%*

Key insights

- This method provides a statistical perspective on the impact of ad exposure. It quantifies how much more likely a user is to convert when exposed to ads compared to the control group.

Limitations

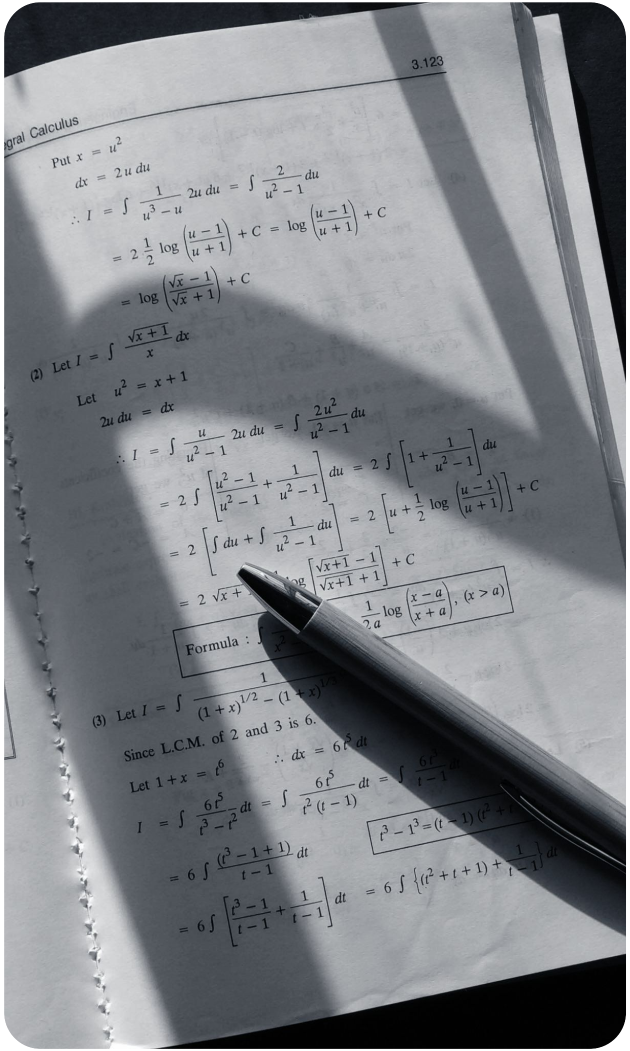
- Attribution approach assumes all conversion rate differences are due to ads, ignoring factors like seasonality or organic trends.
- Odds ratio measures association, not causation—external factors may also influence conversions.

```
Logistic Regression Model:
                           Logit Regression Results
==============================================================================
Dep. Variable:              converted   No. Observations:               588101
Model:                          Logit   Df Residuals:                   588099
Method:                           MLE   Df Model:                            1
Date:                Wed, 05 Mar 2025   Pseudo R-squ.:               0.0004342
Time:                        11:12:52   Log-Likelihood:                -69237.
converged:                       True   LL-Null:                       -69267.
Covariance Type:            nonrobust   LLR p-value:                 8.800e-15
===============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept     -4.0075      0.049    -81.393      0.000      -4.104      -3.911
ad_exposure    0.3661      0.050      7.329      0.000       0.268       0.464
===============================================================================
```

Statistical analysis

Q2 | Code | Odds ratio

```python
import statsmodels.api as sm
from statsmodels.formula.api import logit

# Ensure that 'converted' is numeric (1 for True, 0 for False)
df['converted'] = df['converted'].astype(int)

# Create a binary column for ad exposure (1 for ad, 0 for psa)
df['ad_exposure'] = (df['test group'] == 'ad').astype(int)

# Logistic regression model (ad_exposure vs. converted)
model = logit("converted ~ ad_exposure", data=df).fit()

# Display the regression results
print("\nLogistic Regression Model:")
print(model.summary())

# Calculate Odds Ratio
odds_ratio = np.exp(model.params['ad_exposure'])
print(f"Odds Ratio for ad_exposure: {odds_ratio:.3f}")
```



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Statistical analysis

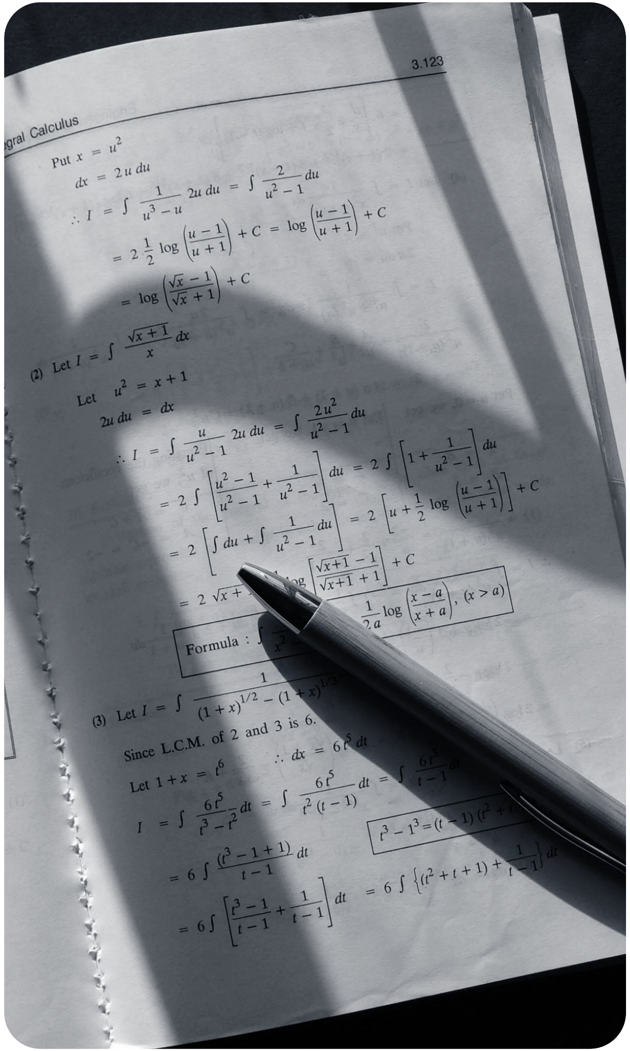
Q2 | Results | Odds ratio

Impact

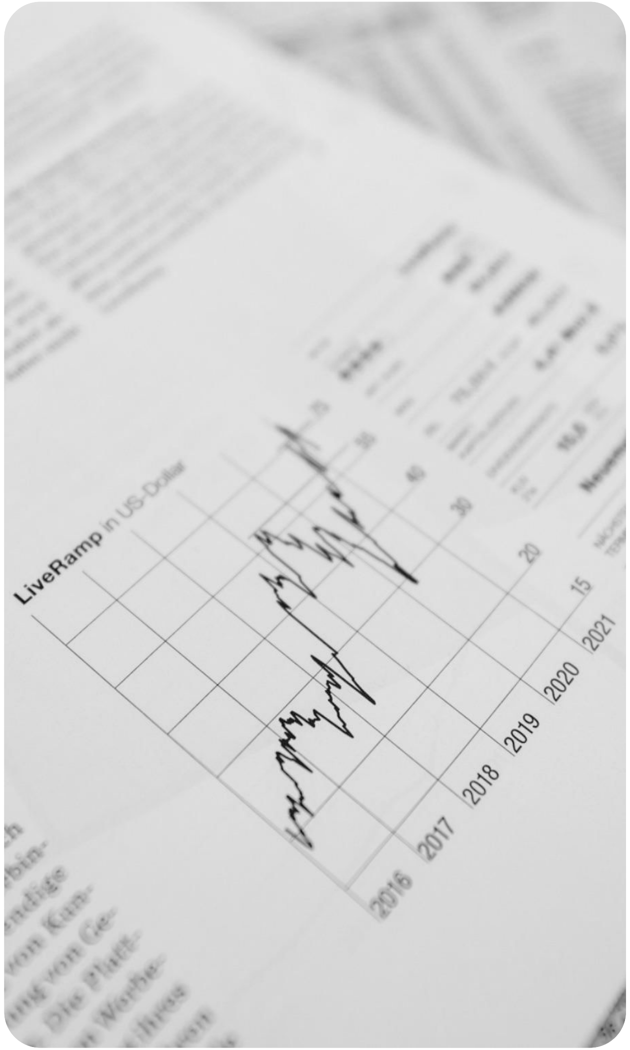
- Odds ratio for 'ad' group: 1.442
- Estimated Attribution to Ads: 44%

Interpretation

- This means that users exposed to ads are 44% more likely to convert compared to users who are exposed to PSAs.
- In other words, the presence of ads significantly increases the likelihood of conversion relative to seeing a PSA.



Findings



Findings

Experiment overview

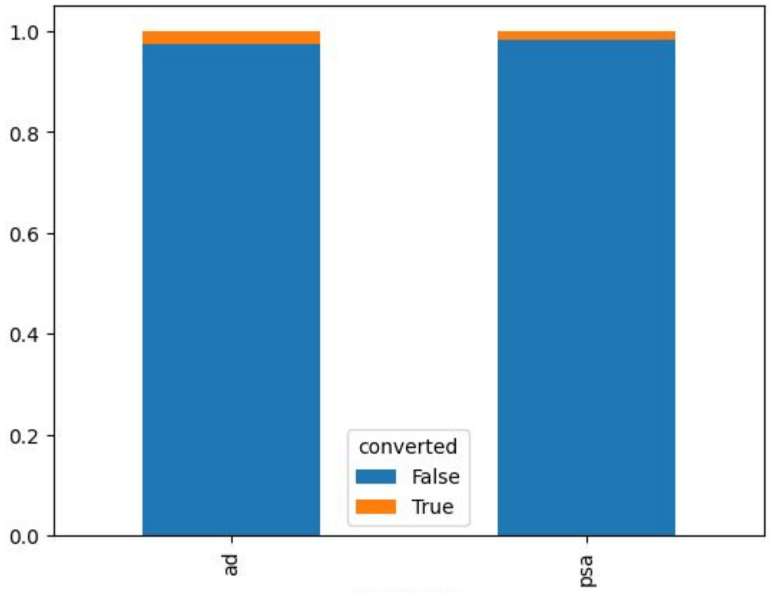
- 🅐 **Control Group:** Sees a Public Service Announcement (PSA) or nothing.
- 🅑 **Experimental Group:** Exposed to ads.

Key findings

- ✅ Campaign Success: Ads lead to a statistically significant improvement in conversions.
- 📊 Ad Effectiveness:
  - **Lift:** 0.75% difference between the control group and the ad group.
  - **Attribution Percentage: 30% increase** in conversions (assuming ads are the only influencing factor).
  - **Odds ratio:** Odds of conversion are **44% higher** for those exposed to ads.

Conclusion

- ✅ **Ads significantly improve conversion rates**, with statistical analysis confirming a higher likelihood of success.



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Appendix


CHRISSY STOCKTON
YOUR SOUL IS A RIVER • NIKITA GILL
What I Didn't Post on Instagram
Edited by Chrissy Stockton
THOUGHT CATALOG Books
HOLLY RIORDAN
SEVERE(D)
THOUGHT CATALOG Books
RANIA NAIM
ALL THE LETTERS I SHOULD HAVE SENT
BRIANNA WIEST
SALT WATER
THOUGHT CATALOG Books
101 ESSAYS that will CHANGE the way YOU THINK
BRIANNA WIEST

Data dictionary

- **index:** Row index
- **user id:** User ID (unique)
- **test group:** If "ad" the person saw the advertisement, if "psa" they only saw the public service announcement
- **converted:** If a person bought the product then True, else is False
- **total ads:** Amount of ads seen by person
- **most ads day:** Day that the person saw the biggest amount of ads
- **most ads hour:** Hour of day that the person saw the biggest amount of ads

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References

- **Boslaugh, S. (2012).** *'Statistics in a Nutshell: A Desktop Quick Reference'.* 2nd edn. Sebastopol, CA: O'Reilly Media, pp. 127–130, 273–279, 312, 367–379.
- **Faviovázquez. (20 Oct 2021).** *'Marketing A/B Testing'.* Kaggle. https://www.kaggle.com/datasets/faviovaz/marketing-ab-testing/data. Last accessed: 02 March 2025
- **Six Sigma Pro SMART. (29 Dec 2023).** *'Complete guide to hands-on A/B Testing | A/B testing in Python | All that you need to know.'* Youtube. https://www.youtube.com/watch?v=AQC7b68H7LU). Last accessed: 02 March 2025

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