Mastery project

Optimizing User Engagement: A/B Testing Insights for Food & Drink Promotion at GloBox

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Abstract

The Growth team at GloBox, an e-commerce marketplace, recently conducted a study focused on boosting awareness and revenue within the food and drink category. Using an A/B test, they introduced a promotional banner for these products to the treatment group, while the control group did not receive the banner.

Our analysis uncovered a statistically significant improvement in user conversion rates for the treatment group, emphasizing the positive impact on customer engagement. While the banner successfully increased conversions, it was observed that it did not have a notable effect on the average spending per user. This insight, backed by statistical data, allows us to fine-tune our strategies for maximum business impact. Recommendations include optimizing product promotion, enhancing the user experience for food and drink shoppers, and continuous monitoring of user behaviour to adapt strategies effectively.

Background

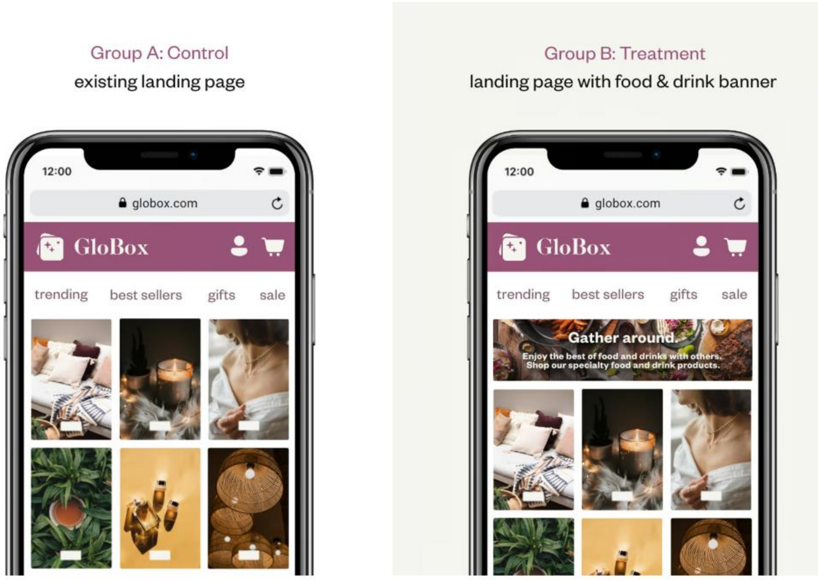
In our data analysis project, we delved into the world of GloBox, an online marketplace renowned for its exclusive fashion and decor items. However, a new focus has emerged food and drink offerings.

Objective

To help GloBox bring this category to the forefront, aiming for increased revenue. To achieve this, GloBox conducted an A/B test, prominently featuring food and drink products with a banner.

The A/B Test: Unveiling GloBox's Strategy

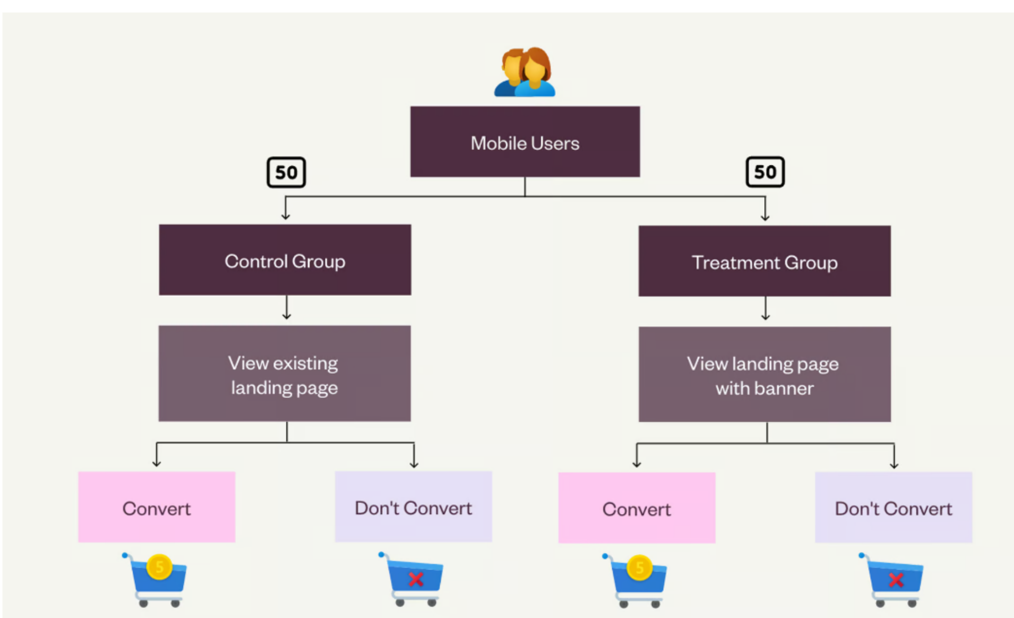
To achieve this objective, GloBox's Growth team initiated an A/B test to gauge the effectiveness of showcasing key products in the food and drink category as a banner at the top of the website. This experiment was specifically conducted on the mobile version of the website. The A/B test was executed as follows:



User Assignment: Users who visited the GloBox main page were randomly assigned to one of two groups: the control group or the test group. The assignment was determined by the date of user entry.

Banner Presentation: For users in the test group, the website loaded with the banner displayed at the top. In contrast, users in the control group did not see the banner.

Conversion Tracking: Subsequently, users had the opportunity to make purchases on the website, either on the same day they joined the experiment or on subsequent days. A "conversion" was registered when a user made one or more purchases.



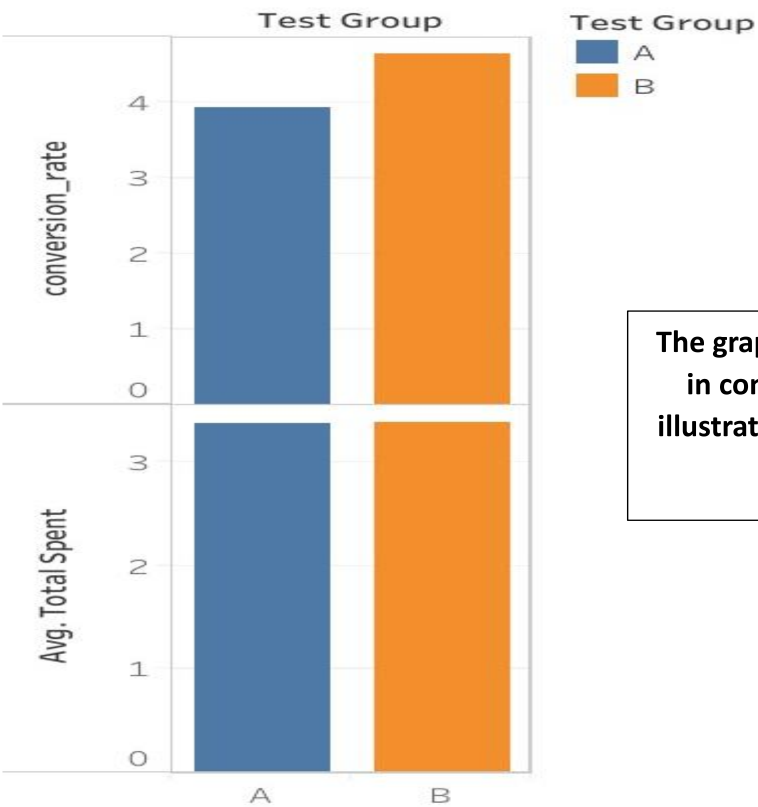
Data processing for analysis

The dataset, extracted and processed using SQL queries , served as the foundation for our analysis. Key details such as user ID, country, gender, device type, test group assignment, conversion status, and total spending were obtained. The extracted information from the query served as the foundation for our strategic analysis. This dataset, critical to our subsequent business insights, took center stage in our exploration of meaningful trends and patterns.

By combining the robustness of statistical analysis with visually intuitive representations, we have uncovered valuable insights that can inform key business decisions and drive impactful outcomes.

Data Visualization

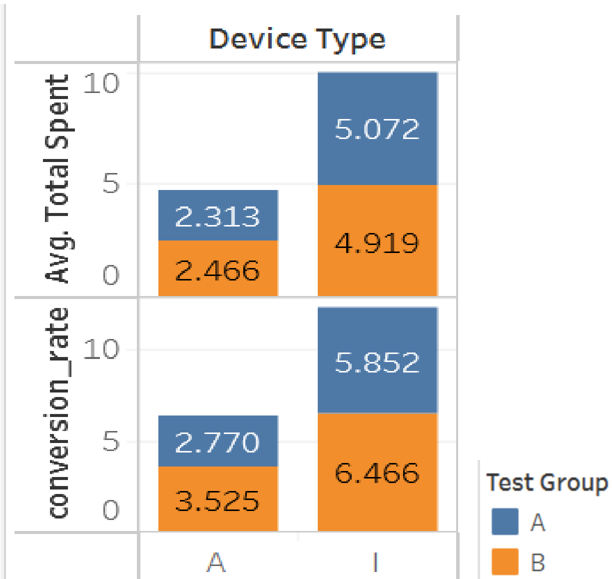
Conversion Rates Discrepancy:
Visualization compares the conversion rate and average amount spent between the test groups



The graph displays a significant difference in conversion rates, yet it does not to illustrate any substantial difference in the average total spending.

iOS vs. Android User Behavior:

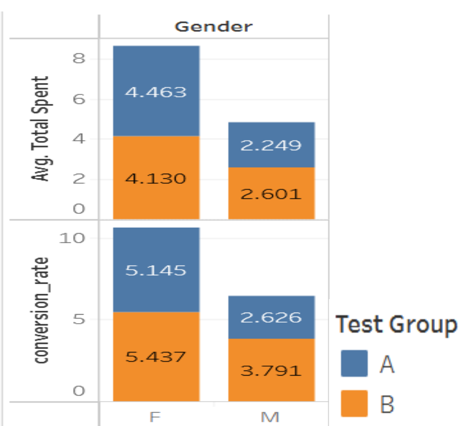
The below graph demonstrates the relationship between the test metrics (conversion rate and average amount spent) and the user's device.



iOS users spend more and have higher conversion rates compared to Android users.

Gender-Based User Dynamics:

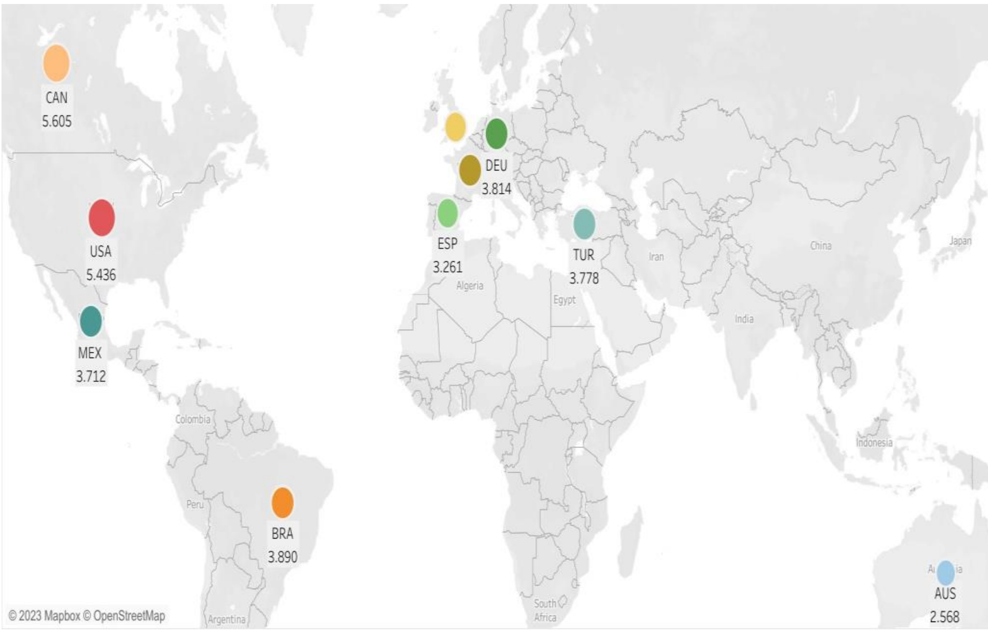
This visual explores the relationship between the test metrics (conversion rate and average amount spent) and the user's gender.



Female users spend more and have higher conversion rates compared to males.

Regional Variation in Conversion Rates and average amount spent:

Visualization explored the relationship between the test metrics (conversion rate and average amount spent) and the user's country.



- **Canada and the USA have the highest conversion rates.**
- **Australia has the lowest conversion rate.**

Analytical Insights

Hypothesis Testing

- *Difference in the [conversion rate] between the two groups:*

We conducted a hypothesis test to examine whether a significant difference exists in the conversion rates between the two groups, utilizing Google Spreadsheets. The assessment was conducted with a significance level of 0.05, a pivotal metric in gauging the statistical relevance of our findings in the business context.

Our hypotheses were explicitly formulated for this study:

- H0 (Null Hypothesis): There is no significant difference between the conversion rates of the two groups.
- H1 (Alternative Hypothesis): There is a significant difference between the conversion rates of the two groups.

We applied hypothesis testing tailored for a difference in proportions, utilizing a two-sample z-test with a pooled proportion. The test statistic was calculated using the following formula derived from the dataset:

- Control Group: 955 Conversions from 24,343 users for a conversion rate of 0.03923099
  Test Group: 1139 Conversions from 24,600 users for a conversion rate of 0.046300813
- Pooled Proportion: (955 + 1139) / (24343 + 24600) = 0.042784464
- Standard Error: √(0.042784464 * (1-0.042784464) * (1 / 24343 + 1 / 24600) = 0.001829526
- Test Statistic: (0.03923099 - 0.046300813) / 0.001829526 = 3.86429177 P-Value: 2 * (1 – NORM.S.DIST(3.86429177, TRUE)) = 0.000111

A p-value below the chosen significance level (0.05) indicates strong evidence against the null hypothesis. Therefore, we reject the null hypothesis and conclude that there is a significant difference in conversion rates between the two groups.

- *Difference in the [average amount spent] per user between the two groups.*

We determined the null and alternative hypothesis:
Ho: There is no difference in the average amount spent per user between Group A and Group B.

H1: There is a difference in the average amount spent per user between Group A and Group B.
Two-sample t-interval with unpooled variance was used for the analysis.

- Control Group average spent is 3.37451752 with a Standard Deviation of 25.93585054 Test Group average spent is 3.390866667 with a Standard Deviation of 25.41358872
- Standard Error: SQRT((25.935850542 / 24343) + (25.413588722 / 24600)) = 0.232135762
- T-Test p-value: 0.943853 (Using T.TEST() function in Excel)

Since the p-value (0.954) is greater than the significance level (0.05), we fail to reject the null hypothesis. This suggests that there is no statistically significant difference in the average amount spent per user between the two groups (Group A and Group B).

Confidence Interval

- *Conversion rate*
  The 95% confidence interval for the difference in the conversion rate between the treatment and control groups (treatment - control) is approximately [0.0035, 0.0107].
  - Standard Error Unpooled: SQRT((0.03923099 * (1 – 0.03923099) / 24343) + (0.046300813 * (1 – 0.046300813) / 24600)) = 0.001828488
  - Difference in Conversion Rates: 0.00706982
  - Lower Bound: 0.00706982 – 1.96 * 0.001828488 = 0.003485985
  - Upper Bound: 0.00706982 + 1.96 * 0.001828488 = 0.010654

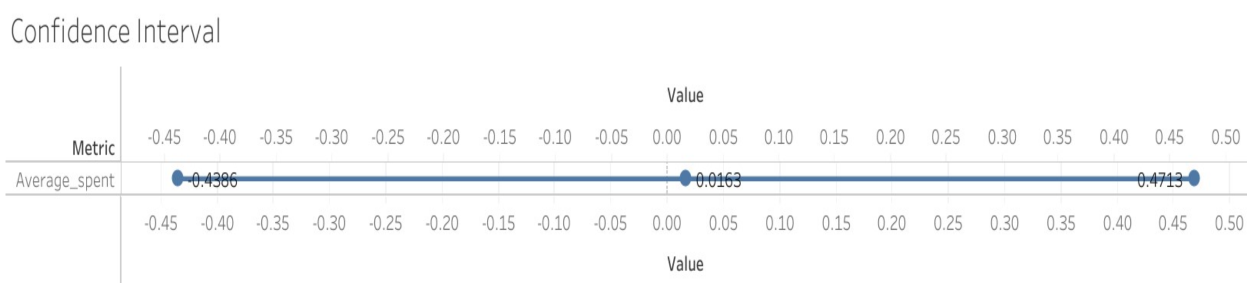
The lower and upper bounds of the confidence interval (CI) represent a range of values within which we can have a high degree of confidence that the true difference in user conversion rates is likely to lie. In this particular analysis, the 95% confidence interval spans from 0.00349 to 0.01065.

- *Average amount spent*

  Here we will calculate the confidence interval for the difference in means of average amount spent between two independent groups (treatment and control). Our approach involves the computation of sample statistics and confidence interval through the following calculations.

  - Sample statistic: Average_total spent group A - Average_total spent group B = -0.016348478
  - Calculation Standard Error:
    Sqrt((Variance treatment /n2-1)+(Variance control/n1-1))
    Sqrt((645.8507/24599)+(672.6687/24342)) = 0.2321405559
  - Lower Bound: Sample Statistic - (Critical Value * Standard Error) = -0.4386
  - Upper Bound: Sample Statistic +(Critical Value * Standard Error) =0.4713

The 95% confidence interval for the difference in means between Group B (treatment) and Group A (control) is approximately (-0.4386, 0.4713). Hence, we can be 95% confident that the true difference in means falls within this interval.



Key highlights of the A/B test analysis

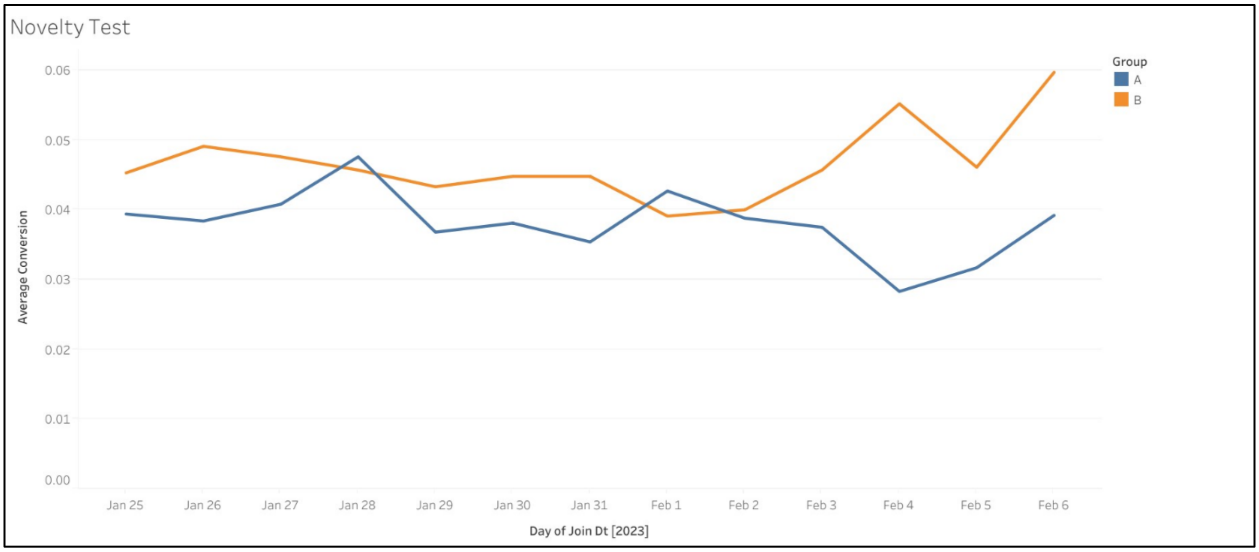
- The A/B test showed a significant increase in user conversion rates for the group exposed to the banner highlighting food and drink products, indicating the banner's effectiveness.
- The 95% confidence interval (0.00349 to 0.01065) reinforces the strong statistical evidence of improved conversion rates due to the banner.
- Average spending per user did not significantly differ between groups, as indicated by a non-significant p-value (0.954) and a confidence interval close to zero (-0.4386 to 0.4713).
- Despite a notable divergence in conversion rates, there is no substantial variance in the reported average total spending.
- iOS users exhibit both higher spending patterns and elevated conversion rates in comparison to their Android counterparts.
- Female users demonstrate a propensity for higher spending and superior conversion rates when compared with their male counterparts.

Additional Analysis

Novelty Effects:

The provided average conversion values for the A/B test between the control group (A) and the treatment group (B) reveal interesting insights. Notably, there is a discernible fluctuation in conversion rates over the observed period. Initially, on January 25, Group B exhibits a higher average conversion rate (0.0453) compared to Group A (0.0394) (Figure below). **This trend continues on subsequent days, with Group B consistently outperforming Group A in terms of conversion rates. The differences in average conversion rates are particularly pronounced on February 4 and 6, where Group B's rates (0.0552 and 0.0597, respectively) are substantially higher than those of Group A.**

This suggests that **the introduction of the promotional banner for the food and drink category on the mobile website positively influences user engagement and leads to higher conversion rates in the treatment group**. The inference drawn is that the promotional strategy is effective in driving user purchases within the specified category. To leverage this finding for further plans, GloBox could consider expanding and optimizing the use of similar promotional strategies or exploring ways to enhance the impact of the banner.



Power Analysis

The power analysis conducted on GloBox's A/B test reveals a crucial aspect of the study. It suggests that in order to detect even subtle improvements in user behavior with a high level of confidence, a larger sample size is necessary. **The analysis recommends a substantial increase in the number of participants, specifically around 124,132 in each group.**

This adjustment ensures a more precise understanding of the impact of the banner showcasing food and drink products on user conversion rates. The significance lies in the fact that a more extensive dataset enhances the reliability of the study findings, providing GloBox with a solid foundation for strategic decision-making. In essence, this insight serves as a strategic imperative, guiding GloBox toward a more informed and impactful implementation of its marketing strategies.

Recommendations

- Given the strong evidence that the banner increased user conversion rates, it is recommended to continue promoting food and drink products prominently on the website. Consider refining and expanding the product selection in this category to further engage users and boost revenue.
- While the banner positively impacted conversion rates, the analysis indicates that it did not significantly affect the average amount spent per user. To address this, focus on enhancing the user experience for food and drink shoppers. This may include:
  - ***Personalized recommendations:*** Tailor product recommendations based on user preferences and past interactions, increasing the likelihood of higher spending.

- ***Improved product visibility:*** Enhance the visibility of food and drink products on the website, making it easier for users to discover and explore these offerings.
- ***Compelling offers to encourage higher spending:*** Create compelling offers, such as discounts, bundles, or loyalty programs, to encourage users to spend more in the food and drink category.

Appendix

https://public.tableau.com/app/profile/ruchika.tiwari2180/viz/GloBox_RT_Relationshiobetweenthetestmetricsandthegender/Dashboard1?publish=yes
https://docs.google.com/spreadsheets/d/1mdNlrd9J9XtlJeQ-AsdW6Sl7il1z2AihX16Qm4ixPfg/edit#gid=165506810
https://docs.google.com/spreadsheets/d/1mdNlrd9J9XtlJeQ-AsdW6Sl7il1z2AihX16Qm4ixPfg/edit#gid=820126340
https://docs.google.com/spreadsheets/d/1mdNlrd9J9XtlJeQ-AsdW6Sl7il1z2AihX16Qm4ixPfg/edit#gid=1902470623
https://docs.google.com/spreadsheets/d/1mdNlrd9J9XtlJeQ-AsdW6Sl7il1z2AihX16Qm4ixPfg/edit#gid=1679551592
https://docs.google.com/spreadsheets/d/1mdNlrd9J9XtlJeQ-AsdW6Sl7il1z2AihX16Qm4ixPfg/edit#gid=461351283
https://public.tableau.com/app/profile/ruchika.tiwari2180/viz/GloBox_RT_Relationshiobetweenthetestmetricsandthegender/CIavg_spentconversion_rate?publish=yes
https://public.tableau.com/app/profile/ruchika.tiwari2180/viz/GloBox_RT_Relationshiobetweenthetestmetricsandthegender/UpdatedNoveltyTest?publish=yes

Comprehensive SQL Code Solutions:

1. Can a user show up more than once in the activity table? Yes or no, and why?

Yes, users may appear more than once in the activity table, if they engage in multiple activities or transactions, they will have multiple entries in the table, resulting in their user ID appearing more than once.

SQL query:
```
SELECT uid, count(*) AS row_count
FROM activity
Group by uid
HAVING count(*) >1
```

2. What type of join should we use to join the users table to the activity table?
Since, we want to include all users from the "users" table and their purchase activity if available, we should use a LEFT JOIN.

SQL Query:
```
SELECT *
FROM activity a
```

```
LEFT JOIN users u ON a.uid=u.id
```

3. What SQL function can we use to fill in NULL values?
To fill in NULL values, we can use the SQL COALESCE() function.

SQL query:
```
SELECT u.id, a.device, a.spent, country, Coalesce (gender, 'unknown') AS gender
FROM activity a
LEFT JOIN users u ON a.uid=u.id
```

4. What are the start and end dates of the experiment?

SQL query:
```
SELECT Min(join_dt) AS start_date, MAX(join_dt) AS end_date
FROM groups
```

5. How many total users were in the experiment?

SQL query:
```
SELECT COUNT(DISTINCT id) AS total_user
FROM users
```

6. How many users were in the control and treatment groups?
We will use the group by clause to determine number of users in each group.

SQL query:
```
SELECT "group", count (distinct u.id) AS total_user
FROM users u
LEFT JOIN groups g ON u.id = g.uid
GROUP BY "group"
```

7. What was the conversion rate of all users?
We used below SQL query to get the conversion rate for all the users

```
Select
    u.id AS user_id,
    u.country,
    u.gender,
    g.device AS device_type,
    g."group" AS test_group,
    CASE WHEN SUM(a.spent) >0 THEN 1 ELSE 0 END AS converter,
    COALESCE(SUM(a.spent), 0) AS total_spent
FROM users u
JOIN groups g ON u.id = g.uid
LEFT JOIN activity a ON u.id=a.uid
```

```
GROUP BY u.id, u.country, u.gender, g.device, g."group";

WITH UserActivity AS (
   SELECT
      u.id AS user_id,
      MAX(CASE WHEN a.uid IS NOT NULL THEN 1 ELSE 0 END) AS converted
   FROM users u
   LEFT JOIN activity a ON u.id = a.uid
   GROUP BY u.id
)
SELECT
   SUM(converted) AS total_conversions,
   COUNT(user_id) AS total_users,
   SUM(converted) * 1.0 / COUNT(user_id) AS conversion_rate
FROM UserActivity;
```

8. What is the user conversion rate for the control and treatment groups?

```
SELECT
   u.test_group AS test_group,
   SUM(u.converted) AS total_conversions,
   COUNT(u.user_id) AS total_users,
   SUM(u.converted) * 1.0 / COUNT(u.user_id) AS conversion_rate
FROM
(
   SELECT
      u.id AS user_id,
      g."group" AS test_group,
      MAX(CASE WHEN a.uid IS NOT NULL THEN 1 ELSE 0 END) AS converted
   FROM users u
   JOIN groups g ON u.id = g.uid
   LEFT JOIN activity a ON u.id = a.uid
   GROUP BY u.id, g."group"
) AS u
GROUP BY u.test_group;
```

9. What is the average amount spent per user?

```
SELECT
   g."group" AS test_group,
   AVG(COALESCE(a.spent, 0.0)) AS average_amount_spent
```

```
FROM users u
LEFT JOIN activity a ON u.id = a.uid
JOIN groups g ON u.id = g.uid
GROUP BY g."group";
```

10. User ID, User's country, user's gender, user's device type, the user's test group, whether or not they converted (spent > $0), and how much they spent in total ($0+).

```
SELECT
   u.id AS user_id,
   u.country,
   u.gender,
   g.device,
   g.group AS test_group,
   CASE WHEN a.spent > 0 THEN 1 ELSE 0 END AS converted,
   SUM(a.spent) AS total_spent
FROM
   users u
LEFT JOIN
   groups g ON u.id = g.uid
LEFT JOIN
   activity a ON u.id = a.uid
GROUP BY
   user_id, country, gender, g.device, test_group, converted;
```

Novelty Test SQL code

```
WITH combined_data as (
SELECT
g.join_dt,
g.group,
u.id,
CASE
WHEN SUM(a.spent) > 0 THEN 1
ELSE 0
END AS converted
FROM users AS u
LEFT JOIN activity AS a
```

ON u.id = a.uid
LEFT JOIN groups AS g
ON g.uid = u.id
GROUP BY
g.join_dt,
g.group,
u.id)
SELECT
join_dt,
"group",
ROUND(AVG(converted),4) AS average_conversion
FROM combined_data
group by 1,2
order by 1,2

Power Analysis codes

```
# I imported my dataset saved in google drive

from google.colab import files
import pandas as pd
uploaded = files.upload()
file_name = list(uploaded.keys())[0]
df = pd.read_csv(file_name)
```

- **query_results-2023-10-11_114430_query_results-2023-10-11_114430.csv**(text/csv) - 1230360 bytes, last modified: 11/15/2023 - 100% done

```
Saving query_results-2023-10-11_114430_query_results-2023-10-11_114430.csv to query_results-2023-10-11_114430_query_results-2023-10-11_114430.csv
```

```
# I used above generated link to import and later explore the data

import pandas as pd
Globox = pd.read_csv('query_results-2023-10-11_114430_query_results-2023-10-11_114430.csv')
Globox.head()
Globox.info()
Globox.describe()
```

```
!pip install statsmodels
```

```
import math
```

```python
from scipy.stats import norm
from scipy.special import erfinv

# Given values
p1 = 0.0392  # Baseline conversion rate
d = 0.00196  # Minimum detectable effect
alpha = 0.05  # Significance level
beta = 0.2  # 1 - Statistical power

# Calculating critical values
z_alpha_2 = abs(math.sqrt(2) * erfinv(2 * alpha - 1))
z_beta = abs(math.sqrt(2) * erfinv(2 * beta - 1))

# Calculating pooled probability
p_bar = p1 + d / 2

# Calculating sample size
n = ((z_alpha_2 * math.sqrt(2 * p_bar * (1 - p_bar)) + z_beta *
math.sqrt(p1 * (1 - p1) + (p1 + d) * (1 - (p1 + d)))) / d) ** 2
n = math.ceil(n)  # Rounding up to the nearest whole number because we
can't have a fraction of a sample

print(f"The required sample size is approximately {n} in each group.")
```