GloBox – A/B Test Report
(Homepage Banner - Food and Drinks)

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➢ Summary

We evaluated a new page banner for food and drink products. The test showed that more people clicked on the banner, but they did not spend more money.

When we looked at the results in more detail, we found that the increase in clicks was higher for Android and Male users, but there was no change in the amount of money they spent. However, when we checked the numbers, we realized that we did not have enough people in the test to detect a 10% change in both the conversion rate and spending. We only had 49,000 users when we needed 185,000. If we want to continue testing, we should use a larger group.

Based on these findings, I recommend not to launch the banner because it did not lead to an increase in spending. If we still want to work on this feature, we should study the results and evaluate it again with more users.

➢ Context

Motivation: The growth team evaluated a homepage banner to promote the food and drink product category. The goal was to increase conversion and revenue by drawing attention to this category.

Test Parameters: We conducted a test involving 48,943 users across ten countries from January 25 to February 6, 2023. The test involved mobile users on Android and iOS.

Test Groups:

- Group A: Control (w/o Banner)
- Group B: Treatment (w/ Banner)

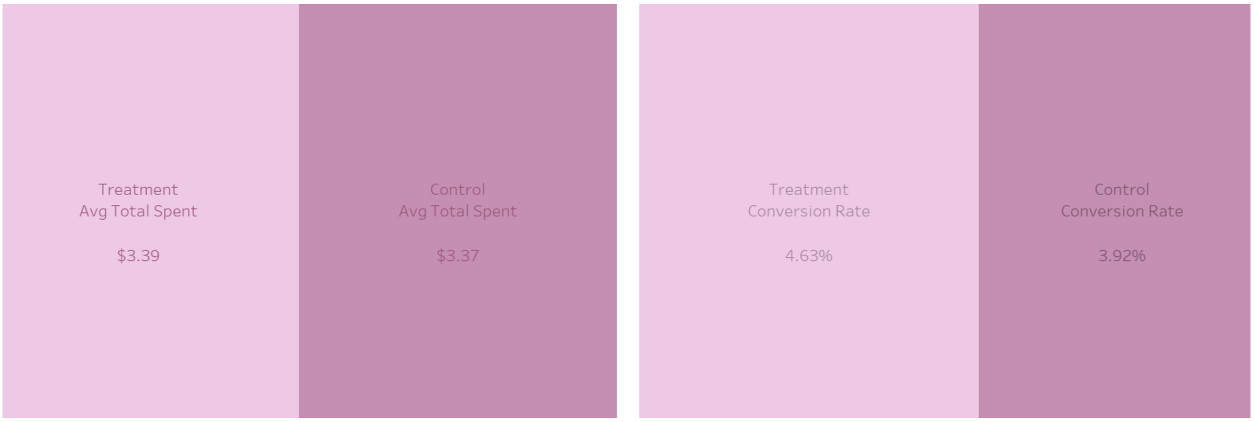
Success Measures:

- User's Conversion Rate
- User's Average Spent

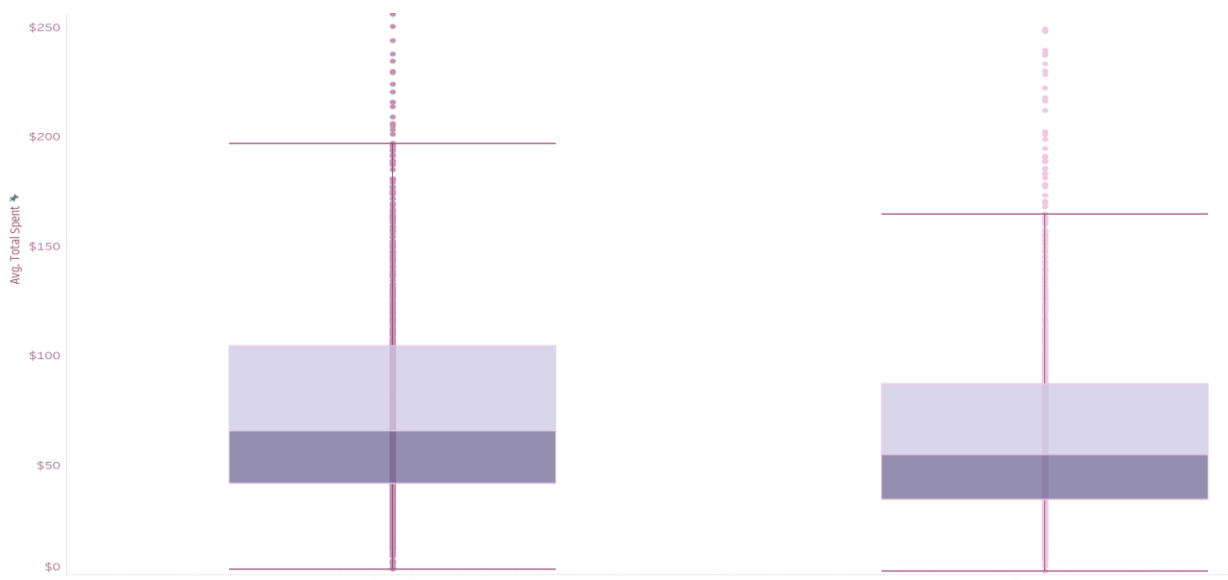
➢ Result

A/B Test: The banner triggered more people making a desired action, but it did not affect how much money they spent. The conversion rate is higher with the banner from 3.92% to 4.63%. This difference is numerically significant. However, the average amount spent per user is similar in both cases ($3.37 in control and $3.39 in treatment) where difference is not numerically significant. Therefore, we can say that the banner increased the conversion rate but did not impact the spending.

- Conversion rate is numerically significant (p = 0.0001 < 5%)
- Average amount spent is not numerically significant (p = 0.95 > 0.05)



Distribution: The banner helped get more people to convert, but surprisingly, those who converted spent less in the group with the banner. A potential reason for not making more profit despite the banner is food and drinks are essential, so people would buy them irrespective of any promotions.



➢ Result Breakdown

Upon conducting a detailed analysis that considers device, gender, country, and region, several notable insights became known.

- *Device:* It is interesting to note that there was a notably higher increase in the conversion rate among Android users when compared to iOS users. This discrepancy in conversion rates based on the device platform used suggests potential variations in user behavior or preferences between Android and iOS users.

- *Gender:* Another captivating observation is conversion rate between male and female users. The analysis indicates that there is more increase in the conversion rate for male users as compared to their female. This discrepancy might be attributed to varying factors such as differing purchase motivations, preferences, or response to promotions.

- *Country and Region:* Zooming in further, an interesting pattern emerges when analyzing conversion rate across different regions. The data reveals that specific geographic regions, such as Australia, Europe, and North America displayed more substantial boost in conversion rate. In contrast, other regions displayed lower increases. These variations in regional conversion rate might be influenced by cultural factors, economic conditions, or the presence of competing market.

Moreover, it is worth noting that despite the differences observed across these divisions, the spending remained consistent. This indicates that while the conversion rate varied, the average amount spent per transaction remained stable across all the analyzed segments.

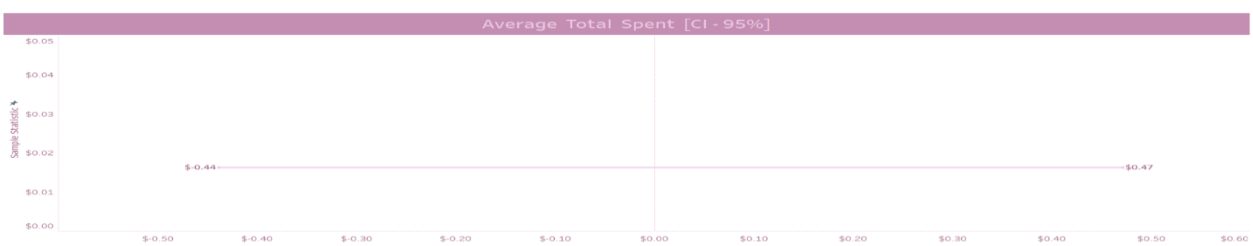
In conclusion, the breakdown of results based on device, gender, country, and region highlights intriguing trends and variations in conversion rates. These insights offer valuable information for further analysis, decision-making and marketing strategies based on specific division.

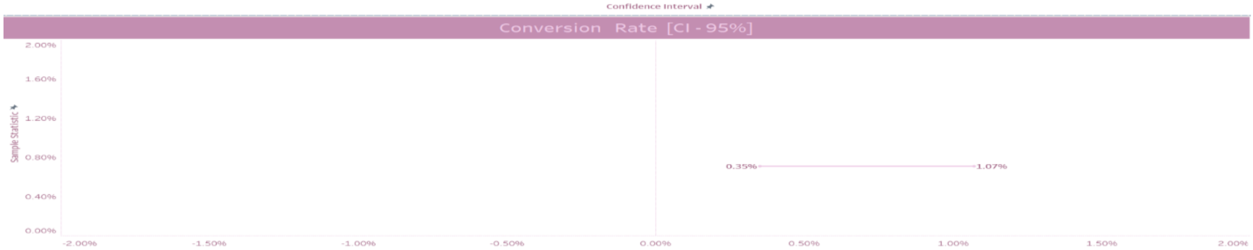
➢ Advanced Task

Confidence Interval:

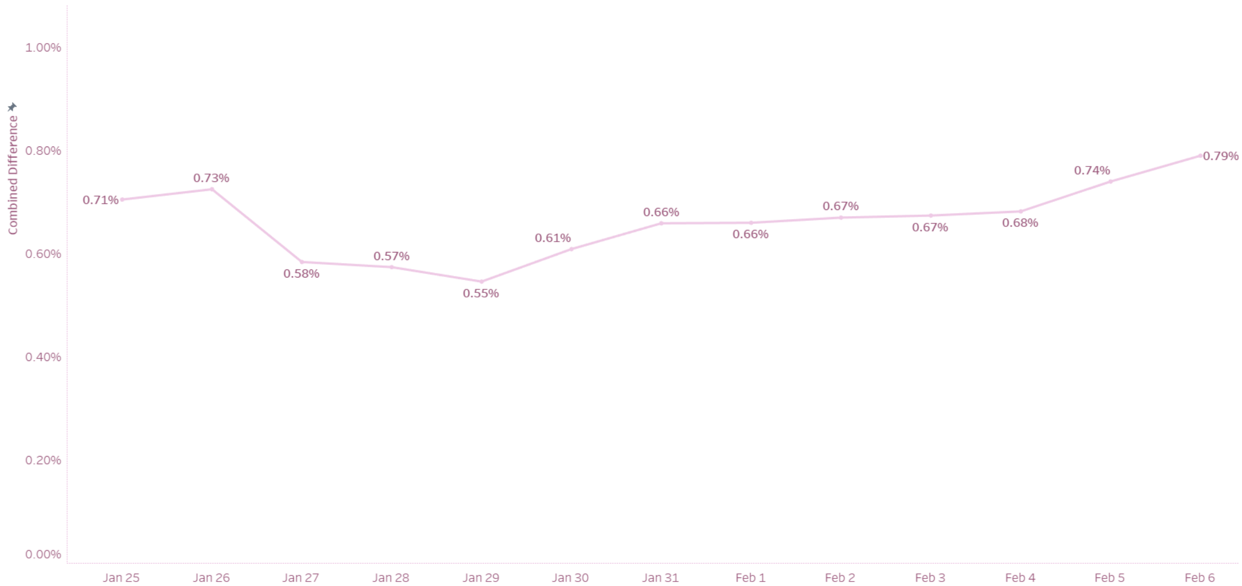
- CI - Conversion Rate: The difference in conversion rate between two groups is numerically significant, with 95% confidence. The range is between 0.35% and 1.07%, where range is not balanced at the center.

- CI - Average Amount Spent: The difference in average amount spent per user between two groups is not numerically significant, with 95% confidence. The range is between -$0.44 and $0.47, and the range is balanced at the center which is zero.





Novelty Effect: There is not evident Novelty Effect in conversion rate. We have compared cumulative conversion rates of both groups to assess overall results of the test.



Power Analysis: The analysis conducted encountered a limitation in terms of sample sizes, which are insufficient to detect a 10% change in the desired metrics. It is worth noting that despite the minimum required sample sizes being set at 185,000 which surpassed the actual number of participants of 49,000. The observed changes were minor and did not exceed the 10% threshold. While it is true that obtaining and processing a larger dataset would have required a considerable amount of time, such an expansion could have presented the opportunity to uncover more meaningful changes in the metrics being evaluated.

Power Analysis - Sample Size		
Measure	Result (both groups)	Details
Conversion Rate	**60.6 k**	* Baseline Conversion Rate: 3.92%
		* MDE: 10%
Average Spent	**185414 k**	* Difference between Means: 0.3375 (10% of control)
		* Expected STDV: 25.9364
* Two sided Size	* Significance Level: 5%	* Power: 80%

➢ Recommendation

Based on the information we have gathered; it is recommended that we refrain from launching this banner. While there was a notable increase in the conversion rate, it did not lead to a notable change in the average amount spent per user. However, if we are determined to continue working on this feature and want to make improvements, we should consider questioning more.

- *Consider the impact on existing products:* We need to evaluate whether the introduction of this feature is affecting the usage or sales of our current product categories. If we find any negative effects, we should modify the user experience accordingly. This could involve adjusting how the feature is presented or integrating it more seamlessly into our overall product offering.

- *Extend the duration of test:* It might be beneficial to run the test for a longer period to gather a larger sample size. Currently, the sample size may not be sufficient to draw accurate conclusions. By extending the test duration, we can increase the number of participants and improve the reliability of our results. It would be ideal to reach a sample size of 185k users.

By following these suggestions, we can gain a better understanding of the feature's potential impact and make informed decisions accordingly.

➢ Appendix

Extract the A/B Test Data

```
SELECT
  u.id AS user_id,
  u.country,
  u.gender,
  g.device AS device,
  g.group AS test_group,
  CASE
    WHEN a.uid IS NULL THEN 0
    ELSE 1
  END AS converted,
  COALESCE(SUM(a.spent), 0) 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
  u.id,
  u.country,
  u.gender,
  g.device,
  g.group,
  a.uid
ORDER BY   u.id;
```

Novelty Effect

```
WITH subquery AS (
  SELECT g.join_dt, g.group, COUNT(DISTINCT u.id) AS user_count
  FROM groups g
  INNER JOIN users u ON g.uid = u.id
  GROUP BY g.join_dt, g.group
),
converted_users AS (
  SELECT a.dt, g.group, COUNT(DISTINCT g.uid) AS converted_user_count
  FROM activity a
  INNER JOIN groups g ON a.uid = g.uid AND a.device = g.device
  GROUP BY a.dt, g.group
),
combined_data AS (
  SELECT s.join_dt, s.group, s.user_count, cu.converted_user_count,
         SUM(s.user_count) OVER (PARTITION BY s.group ORDER BY s.join_dt) AS cum_users,
         SUM(cu.converted_user_count) OVER (PARTITION BY cu.group ORDER BY cu.dt) AS
cum_converted_users
  FROM subquery s
  LEFT JOIN converted_users cu ON s.group = cu.group AND s.join_dt = cu.dt
)
SELECT cd.join_dt AS "DATE",
       SUM(CASE WHEN cd.group = 'A' THEN cd.user_count ELSE 0 END) AS "A_COUNT",
       SUM(CASE WHEN cd.group = 'B' THEN cd.user_count ELSE 0 END) AS "B_COUNT",
       SUM(CASE WHEN cd.group = 'A' THEN cd.converted_user_count ELSE 0 END) AS "A_CONVERTED",
       SUM(CASE WHEN cd.group = 'B' THEN cd.converted_user_count ELSE 0 END) AS "B_CONVERTED",
       ROUND((SUM(CASE WHEN cd.group = 'A' THEN cd.cum_converted_users ELSE 0 END) / SUM(CASE
WHEN cd.group = 'A' THEN cd.cum_users ELSE 0 END)), 5) AS "A_COMBINED_CONVERSION_RATE",
       ROUND((SUM(CASE WHEN cd.group = 'B' THEN cd.cum_converted_users ELSE 0 END) / SUM(CASE
WHEN cd.group = 'B' THEN cd.cum_users ELSE 0 END)), 5) AS "B_COMBINED_CONVERSION_RATE",
       ROUND(((SUM(CASE WHEN cd.group = 'B' THEN cd.cum_converted_users ELSE 0 END) / SUM(CASE
WHEN cd.group = 'B' THEN cd.cum_users ELSE 0 END)) -
       (SUM(CASE WHEN cd.group = 'A' THEN cd.cum_converted_users ELSE 0 END) / SUM(CASE WHEN
cd.group = 'A' THEN cd.cum_users ELSE 0 END))), 5) AS "COMBINED_DIFFERENCE"
FROM combined_data cd
GROUP BY cd.join_dt
ORDER BY cd.join_dt;
```

Tableau Link

https://public.tableau.com/app/profile/sneha.tayde.nov27/viz/Project-GLOBOX/Project-GLOBOX

*** Query for Join Curve is included in the **GloBox (SQL).pdf** document.*
*** Visualization for Join Curve is included in the Tableau Link.*