

FACEBOOK CAMPAIGN ANALYSIS

January 2023

BY: AMR ELLAKANY



amrellakany600@gmail.com



<https://amr-ellakany.jimdosite.com/>





CONTENT

- 01** Terminology Defining
- 02** Dataset Exploring
- 03** Campaign Highlights
- 04** Lookalike vs Detailed Targeting
- 05** Various Funnel Metrics
- 06** Statistics & Charts

PROJECT'S LINK:
[Click to Explore The Code](#)

A photograph of a modern office environment. Several people are gathered around a large white conference table, engaged in a discussion. One person in the foreground is gesturing while speaking. The office has large windows in the background, letting in natural light. A large graphic of the word "TERMINOLOGY" is overlaid on the image, with a smaller "DEFINING" graphic positioned below it.

TERMINOLOGY

DEFINING

THE MARKETING FUNNEL

01

Awareness

02

Interest

03

Desire

03

Action

AUDIENCE

01

Core (Detailed Targeting)

02

Lookalike

03

Custom (Hot & Warm)



DATA SET EXPLORING

THE DATASET

```
In [104]: import pandas as pd  
df = pd.read_csv(r"C:\Users\user\Desktop\FB Campign analysis\A Marketing campaign Dataset.csv")  
df.head()
```

Out[104]:

| | Reporting Starts | Reporting Ends | Ad Set Name | Amount Spent | Results | Result indicator | CPR | Reach | Impressions | Frequency | CPM | CPC | CTR |
|---|------------------|----------------|-----------------------------|--------------|---|------------------|-------|--------|-------------|-----------|----------|----------|------|
| 0 | 20/5/2022 | 31/5/2022 | T1 - Cold - LLA - Promo May | 332.65 | 2 actions:offsite_conversion.fb_pixel_purchase | 166.3250 | 6032 | 12594 | 2.087865 | 26.413371 | 2.294138 | 2.20 | |
| 1 | 20/5/2022 | 31/5/2022 | T1 - Cold - DT - Promo May | 915.00 | 15 actions:offsite_conversion.fb_pixel_purchase | 61.0000 | 18900 | 42510 | 2.249206 | 21.524347 | 2.636888 | 1.58 | |
| 2 | 20/5/2022 | 31/5/2022 | T2 - Cold - LLA - Promo May | 327.77 | 4 actions:offsite_conversion.fb_pixel_purchase | 81.9425 | 34743 | 61268 | 1.763463 | 5.349775 | 0.947312 | 1.23 | |
| 3 | 20/5/2022 | 31/5/2022 | T2 - Cold - DT - Promo May | 297.38 | 0 | NaN | NaN | 45001 | 65880 | 1.463967 | 4.513965 | 0.788806 | 1.22 |
| 4 | 20/5/2022 | 31/5/2022 | T3 - Cold - LLA - Promo May | 291.45 | 4 actions:offsite_conversion.fb_pixel_purchase | 72.8625 | 69040 | 147600 | 2.137891 | 1.974594 | 0.464092 | 1.11 | |



THE DATASET

Ad Set Overview

- Cold, Warm, and Hot ad sets
- lookalike & Detailed Targeting in Cold ad set
- T1, T2, T3, and T4 in Cold Ad set
- CRSLS & Videos in Warm Ad set
- Last chance, Discount, and Last day in Hot ad set

```
In [6]: (df['Ad Set Name']).unique()
```

```
Out[6]: array(['T1 - Cold - LLA - Promo May', 'T1 - Cold - DT - Promo May',
   'T2 - Cold - LLA - Promo May', 'T2 - Cold - DT - Promo May',
   'T3 - Cold - LLA - Promo May', 'T3 - Cold - DT - Promo May',
   'T4 - Cold - DT - Promo May', 'T4 - Cold - LLA - Promo May',
   'Warm - CRSLS', 'Warm - Videos', 'HOT - Last day',
   'HOT - Last chance & crsl', 'HOT - Discount'], dtype=object)
```

CREATING A CATEGORY COLUMN FOR DIFFERENT AD SETS

Hot, Warm, and Cold Ad Sets

```
In [70]: def categorize_ad_set(ad_set_name):
    if 'Warm' in ad_set_name:
        return 'Warm'
    elif 'HOT' in ad_set_name:
        return 'Hot'
    else:
        return 'Cold'

df['Category'] = df['Ad Set Name'].apply(categorize_ad_set)
df.head()
```

Out[70]:

| Amount Spent | Results | Result indicator | CPR | Reach | Impressions | Frequency | CPM | CPC | CTR (all) | Link Clicks | Landing Page Views | Category | |
|--------------|---------|--|----------|-------|-------------|-----------|-----------|----------|-----------|-------------|--------------------|----------|------|
| 332.65 | 2 | actions:offsite_conversion.fb_pixel_purchase | 166.3250 | 6032 | 12594 | 2.087865 | 26.413371 | 2.294138 | 2.207400 | 145 | 89 | Cold | |
| 915.00 | 15 | actions:offsite_conversion.fb_pixel_purchase | 61.0000 | 18900 | 42510 | 2.249206 | 21.524347 | 2.636888 | 1.587862 | 347 | 215 | Cold | |
| 327.77 | 4 | actions:offsite_conversion.fb_pixel_purchase | 81.9425 | 34743 | 61268 | 1.763463 | 5.349775 | 0.947312 | 1.237187 | 346 | 220 | Cold | |
| 297.38 | 0 | | NaN | NaN | 45001 | 65880 | 1.463967 | 4.513965 | 0.788806 | 1.220401 | 377 | 225 | Cold |

CREATING A SUB-CATEGORY COLUMN FOR DIFFERENT AD SETS INSIDE COLD AD SET

Looalike vs Detailed Targeting

```
In [20]: df['Ad Set Name'].unique()
```

```
Out[20]: array(['T1 - Cold - LLA - Promo May', 'T1 - Cold - DT - Promo May',
   'T2 - Cold - LLA - Promo May', 'T2 - Cold - DT - Promo May',
   'T3 - Cold - LLA - Promo May', 'T3 - Cold - DT - Promo May',
   'T4 - Cold - DT - Promo May', 'T4 - Cold - LLA - Promo May',
   'Warm - CRSL', 'Warm - Videos', 'HOT - Last day',
   'HOT - Last chance & crsl', 'HOT - Discount'], dtype=object)
```

```
In [105]: def categorize_ad_set_2(ad_set_name):
    if('DT' in ad_set_name):
        return 'Detailed Targeting'
    elif('LLA' in ad_set_name):
        return 'Lookalike Audience'
    else:
        return 'Other'
```

```
df['Subcategory'] = df['Ad Set Name'].apply(categorize_ad_set_2)
df.head()
```

```
Out[105]:
```

| mount Spent | Results | Result Indicator | CPR | Reach | Impressions | Frequency | CPM | CPC | CTR (all) | Link Clicks | Landing Page Views | Subcategory |
|----------------|---------|--|----------|-------|-------------|-----------|-----------|----------|-----------|----------------|--------------------------|--------------------|
| 332.65 | 2 | actions:offsite_conversion.fb_pixel_purchase | 166.3250 | 6032 | 12594 | 2.087865 | 26.413371 | 2.294138 | 2.207400 | 145 | 89 | Lookalike Audience |
| 915.00 | 15 | actions:offsite_conversion.fb_pixel_purchase | 61.0000 | 18900 | 42510 | 2.249206 | 21.524347 | 2.636888 | 1.587862 | 347 | 215 | Detailed Targeting |



CAMPAIGN HIGHLIGHTS

CAMPAIGN HIGHLIGHTS

- We reached around **450K** unique people.
- Approx **1.1 million** impressions.
- Each person saw the ad around **2.5** times.
- Approx **5.6K** link clicks and **2.9K** landing page views.
- A total of **83** results.
- Spent **4,362 EUR**.

```
In [69]: df[["Reach","Impressions","Link Clicks","Landing Page Views","Results","Amount Spent"]].sum()
```

```
Out[69]: Reach           453534.00
          Impressions    1136052.00
          Link Clicks     5589.00
          Landing Page Views 2985.00
          Results          83.00
          Amount Spent     4362.12
          dtype: float64
```

AGGREGATING ALL METRICS BASED ON THE CATEGORY

```
In [72]: results = df.groupby('Category').agg({'Reach':'mean','Impressions':'mean',
                                             'CTR (all)':'mean','Results':'mean',
                                             'CPR':'mean'})
results
```

Out[72]:

| Category | Reach | Impressions | CTR (all) | Results | CPR |
|----------|--------------|---------------|-----------|-----------|-----------|
| Cold | 44435.375000 | 79417.500000 | 1.370799 | 4.000000 | 80.352667 |
| Hot | 11195.666667 | 58889.666667 | 1.034126 | 10.333333 | 38.851667 |
| Warm | 32232.000000 | 162021.500000 | 1.052970 | 10.000000 | 51.310357 |

REACH

Cold ad set has the **highest** reach, indicating success in reaching a broad audience.

IMPRESSIONS

Warm ad set generates the **highest** impressions, surpassing Cold, **despite** a smaller reach.

CTR

Cold Ad sets show **higher** CTR, possibly due to less familiarity with the company's content.

HOT & WARM PERFORMANCE

They perform **the best**, aligning with expectations of higher familiarity and conversion **likelihood**.

CPR

Hot Ad set has the **lowest** CPR, indicating **cost-effectiveness**, likely due to a closer audience ready for purchase as they are more familiar.

AGGREGATING ALL METRICS BASED ON THE SUB-CATEGORY

```
In [74]: df_cold = df[df['Category']=='Cold']

In [75]: df_cold = df_cold.groupby('Subcategory').agg({'Reach':'mean', 'Impressions':'mean',
                                                    'CTR (all)':'mean', 'Results':'mean',
                                                    'CPR':'mean'})
```

```
df_cold
```

Out[75]:

| Subcategory | Reach | Impressions | CTR (all) | Results | CPR |
|--------------------|----------|-------------|-----------|---------|---------|
| Detailed Targeting | 34033.25 | 53142.25 | 1.351996 | 4.25 | 53.2550 |
| Lookalike Audience | 54837.50 | 105692.75 | 1.389602 | 3.75 | 93.9015 |

LOOKALIKE VS DETAILED TARGETING



LOOKALIKE VS DETAILED TARGETING

[UNPIVOTING & PLOTTING]

```
In [77]: df_transformed = df_cold.reset_index().melt('Subcategory')
df_transformed
```

Out[77]:

| | Subcategory | variable | value |
|---|--------------------|-------------|---------------|
| 0 | Detailed Targeting | Reach | 34033.250000 |
| 1 | Lookalike Audience | Reach | 54837.500000 |
| 2 | Detailed Targeting | Impressions | 53142.250000 |
| 3 | Lookalike Audience | Impressions | 105692.750000 |
| 4 | Detailed Targeting | CTR (all) | 1.351996 |
| 5 | Lookalike Audience | CTR (all) | 1.389602 |
| 6 | Detailed Targeting | Results | 4.250000 |
| 7 | Lookalike Audience | Results | 3.750000 |
| 8 | Detailed Targeting | CPR | 53.255000 |
| 9 | Lookalike Audience | CPR | 93.901500 |

```
In [83]: viz = sns.FacetGrid(df_transformed, col='variable', col_wrap=3, sharex=False,
                           sharey=False, height=4)
```

```
viz.map(sns.barplot, 'Subcategory', 'value', order=df_cold.reset_index()['Subcategory'])
```

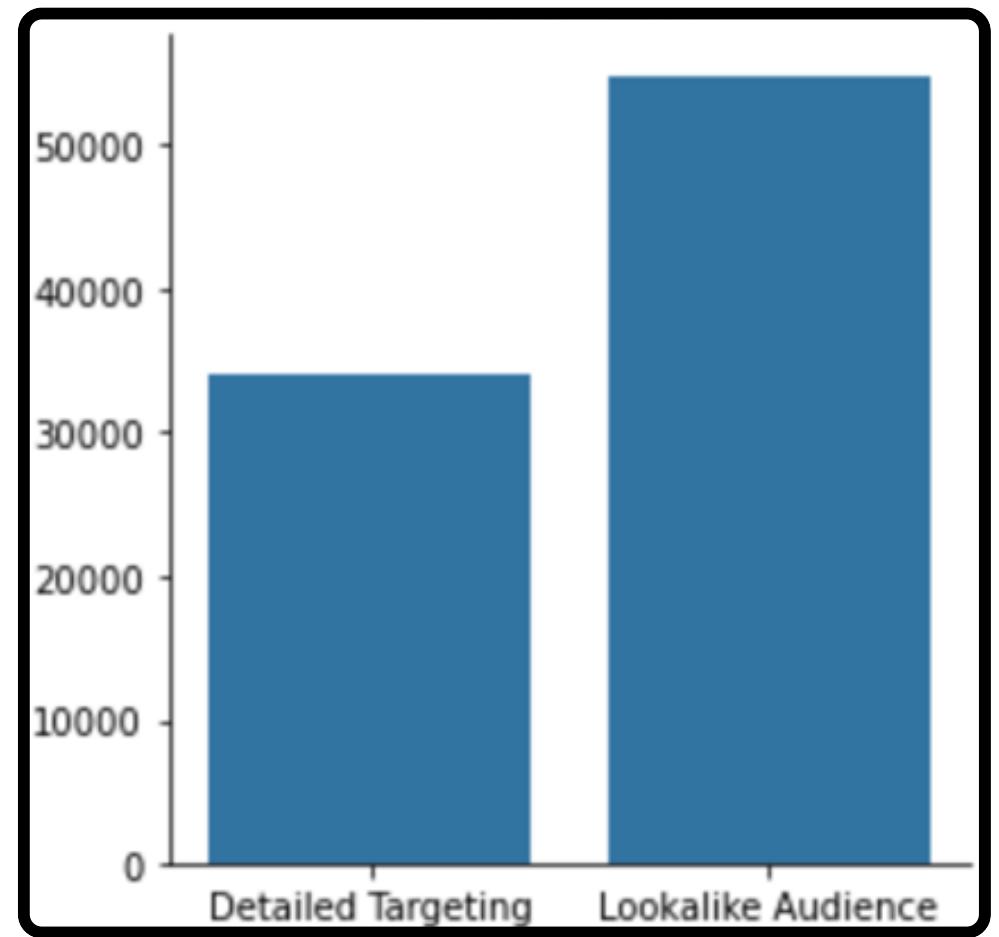
```
plt.show()
```

LOOKALIKE VS DETAILED TARGETING

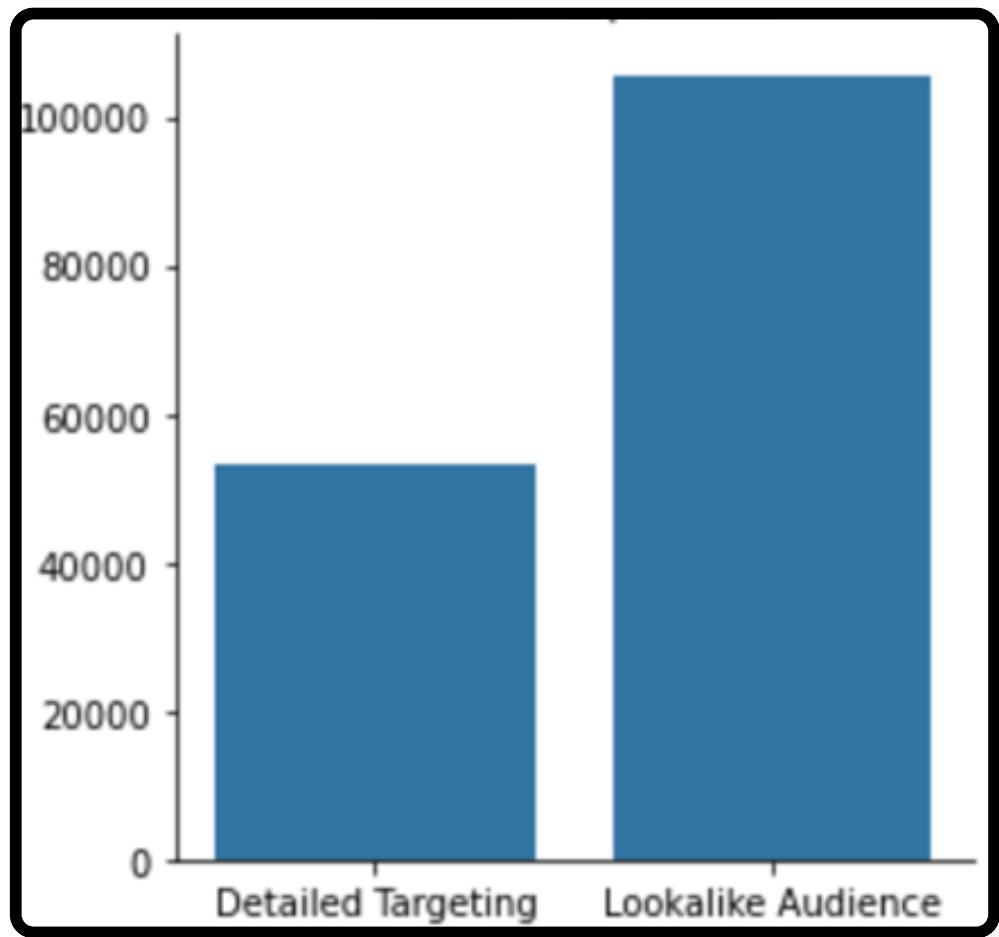
[REACH & IMPRESSION]

- **Reach & Impression**

The Lookalike audience has a **higher reach** and **impressions** compared to the Detailed audience, as Lookalikes resemble a similar base as the existing audience.



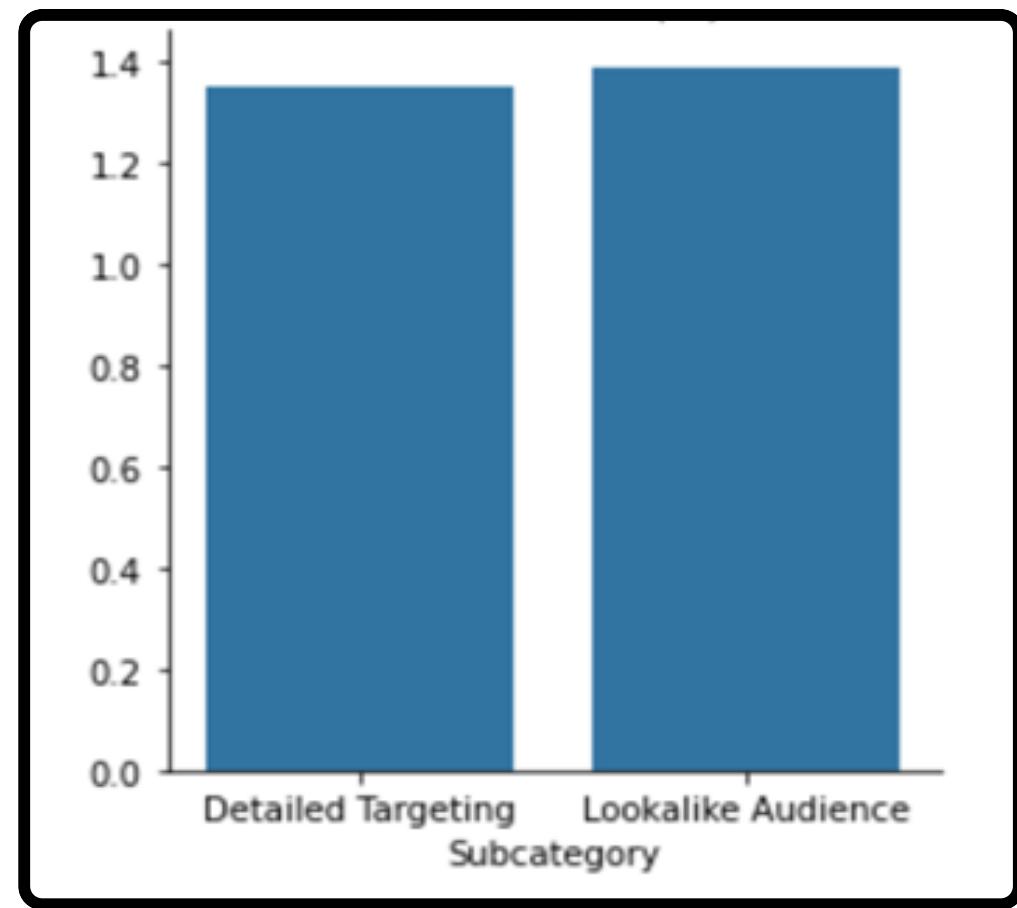
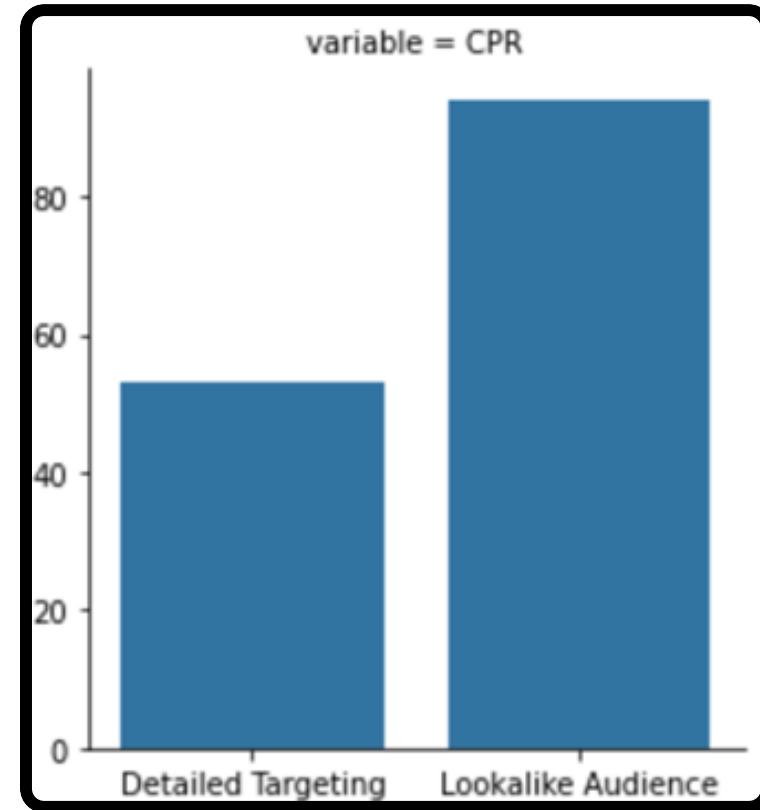
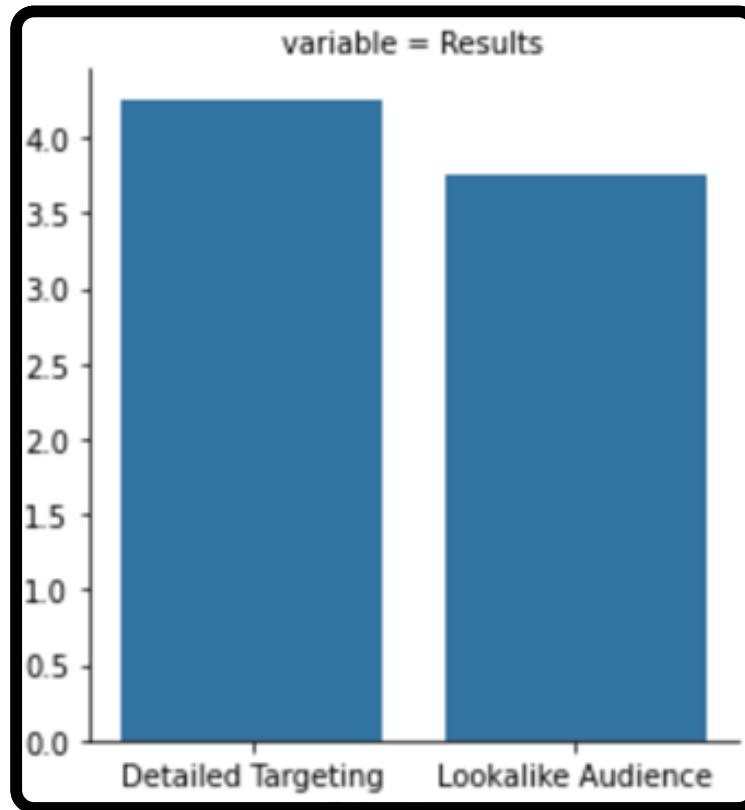
Reach



Impression

LOOKALIKE VS DETAILED TARGETING

[RESULTS, CPR, AND CTR]



- **Results & CPR**

- **Detailed** audiences achieve **more results** (conversions) than **Lookalike**.
- **Detailed** audiences have a **lower cost** for conversions compared to **Lookalike**.

- **CTR (Click-Through Rate)**

No significant differences in CTR were observed; both audiences engage equally with the content.

LOOKALIKE VS DETAILED TARGETING

[CONCLUSION]

- **Lookalike audiences**
 - They are **more extensive** and **suitable** for **brand awareness campaigns**.
- **Detailed audiences**
 - Despite being **smaller**, are more **likely to convert**, making them ideal for **conversion-focused campaigns**.

VARIOUS FUNNEL METRICS

VARIOUS FUNNEL METRICS PLOTS CODING

TOP FUNNEL METRICS

```
In [89]: def top_funnel_metrics(df):
    fig,axs = plt.subplots(1, 3, figsize=(23,5))

    sns.barplot(x='Ad Set Name', y='Reach', data=df, ax=axs[0])
    axs[0].set_title('Reach')

    sns.barplot(x='Ad Set Name', y='Impressions', data=df, ax=axs[1])
    axs[1].set_title('Impressions')

    sns.barplot(x='Ad Set Name', y='CPM', data=df, ax=axs[2])
    axs[2].set_title('CPM')

    for ax in axs:
        for label in ax.get_xticklabels():
            label.set_rotation(90)

    plt.show()

top_funnel_metrics(df_hot)
```

MIDDLE FUNNEL METRICS

```
In [90]: def mid_funnel_metrics(df):
    fig, axs = plt.subplots(1, 3, figsize=(23,5))

    sns.barplot(x='Ad Set Name', y='CTR (all)', data=df, ax=axs[0])
    axs[0].set_title('CTR (all)')

    sns.barplot(x='Ad Set Name', y='Landing Page Views', data=df, ax=axs[1])
    axs[1].set_title('Landing Page Views')

    sns.barplot(x='Ad Set Name', y='CPC', data=df, ax=axs[2])
    axs[2].set_title('CPC')

    for ax in axs:
        for label in ax.get_xticklabels():
            label.set_rotation(90)

    plt.show()

mid_funnel_metrics(df_hot)
```

BOTTOM FUNNEL METRICS

```
In [91]: def bottom_funnel_metrics(df):
    fig, axs = plt.subplots(1, 2, figsize=(23,5))

    sns.barplot(x='Ad Set Name', y='Results', data=df, ax=axs[0])
    axs[0].set_title('Results')

    sns.barplot(x='Ad Set Name', y='CPR', data=df, ax=axs[1])
    axs[1].set_title('CPR')

    for ax in axs:
        for label in ax.get_xticklabels():
            label.set_rotation(90)

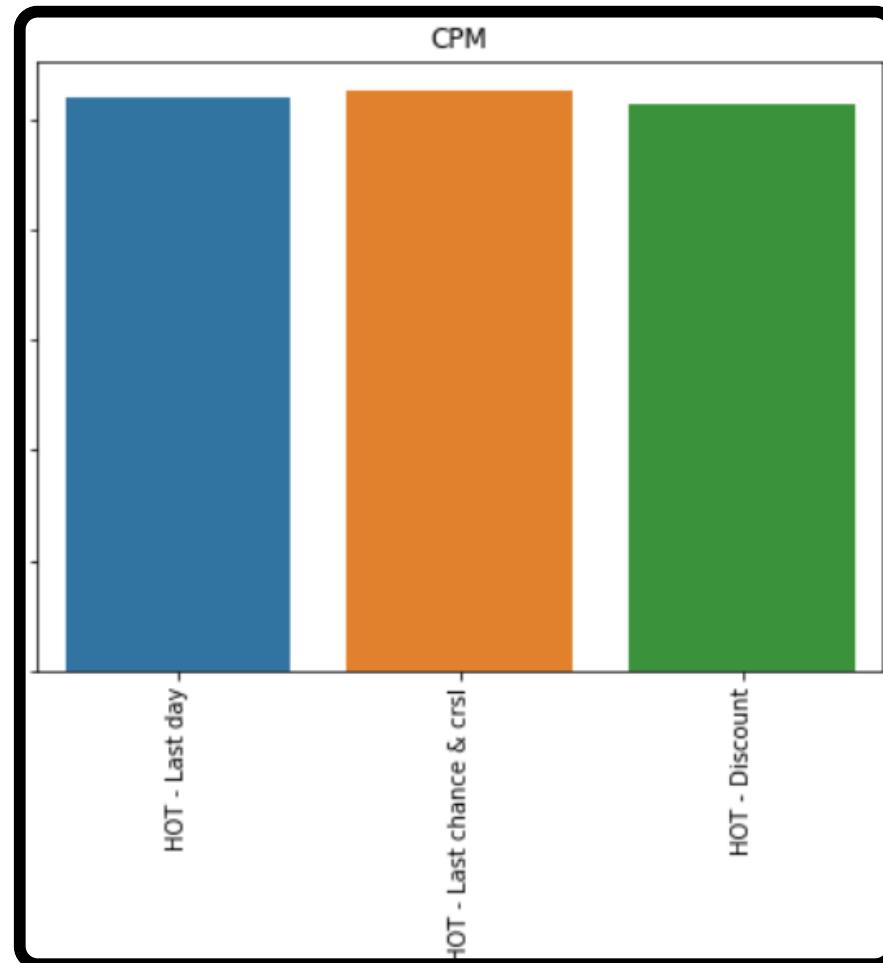
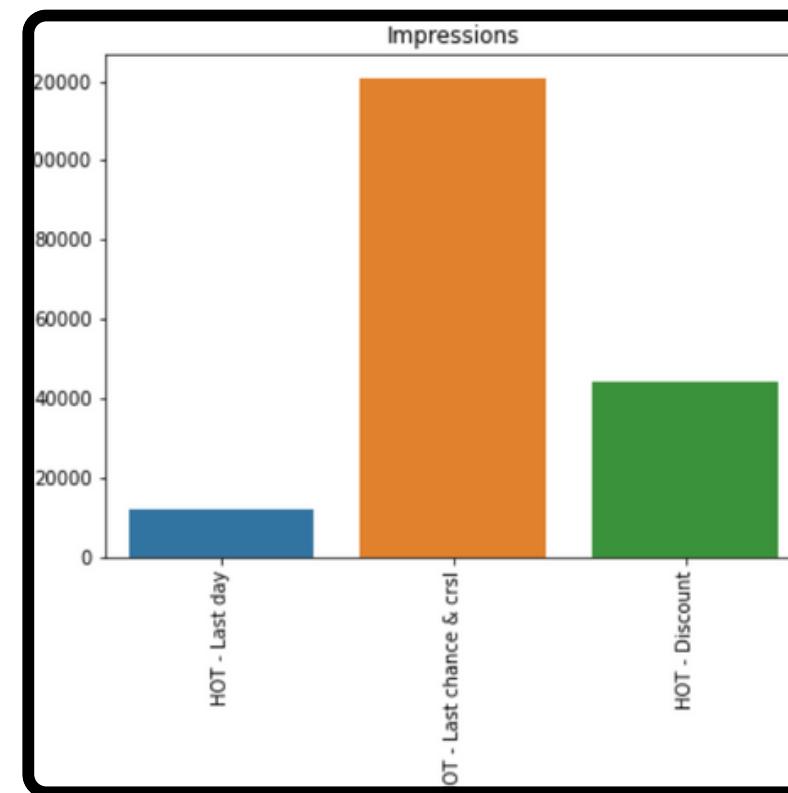
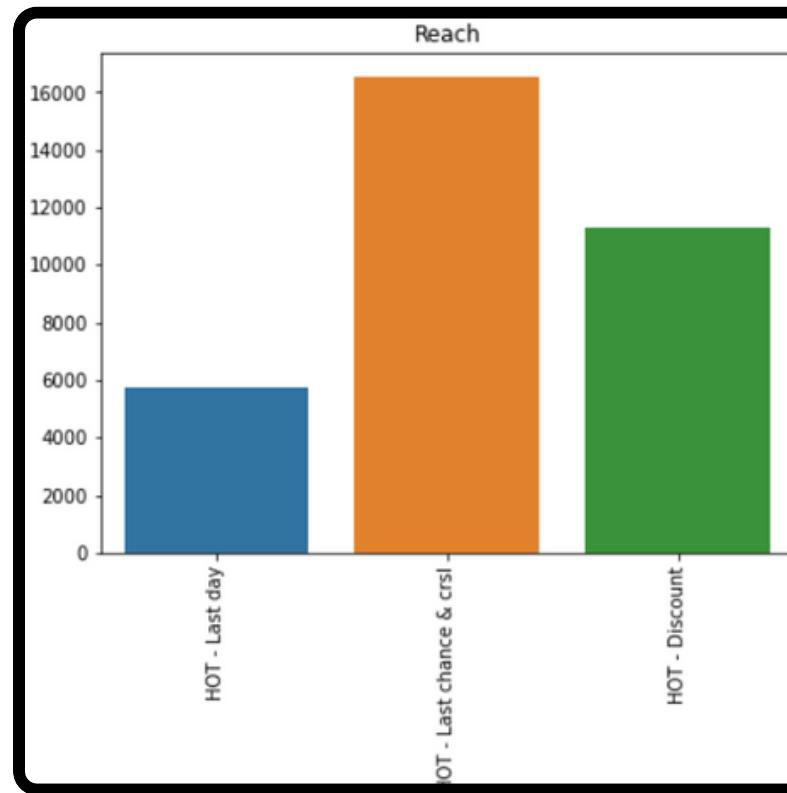
    plt.show()

bottom_funnel_metrics(df_hot)
```

STATISTICS & CHARTS

TOP FUNNEL METRICS ANALYSIS

[HOT AD SET]



- **Reach & Impression**

The ad set (**Last - Chance & Crsl**) outperforms others with **higher reach** and **impressions**, indicating a **wider user reach**.

- **CTR (Click-Through Rate)**

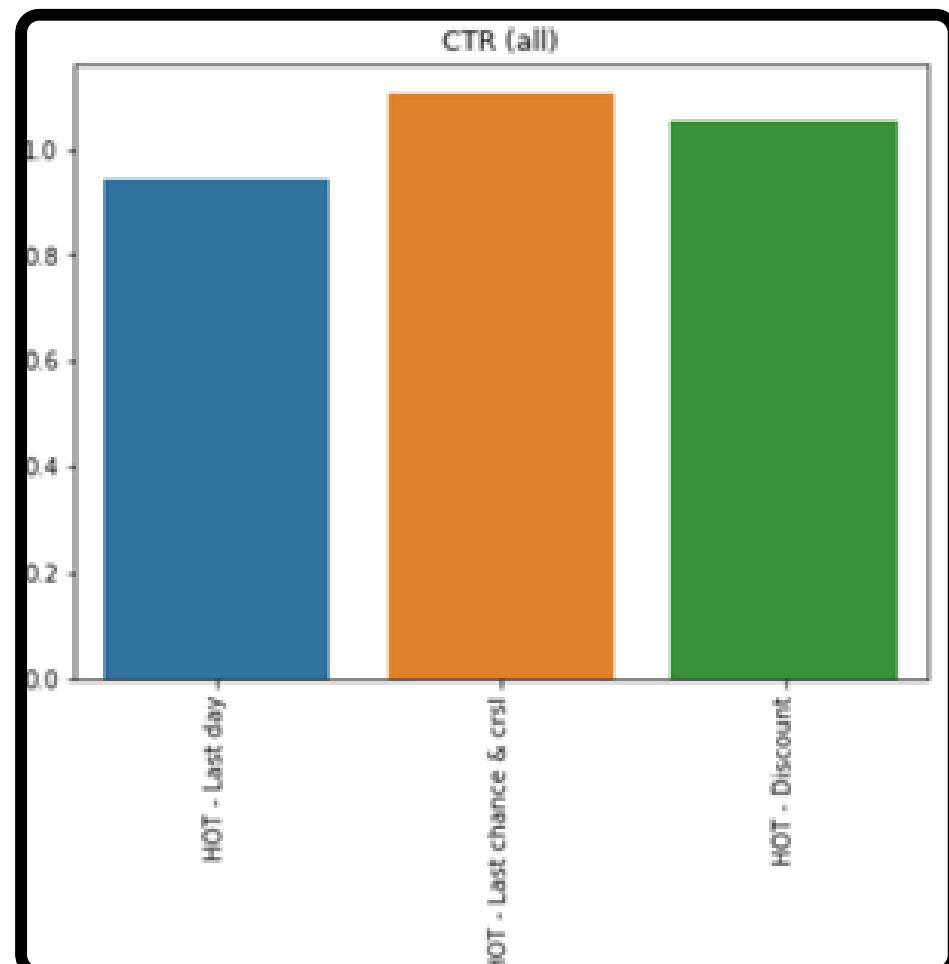
All **three** ad sets exhibit **similar costs per 1000 impressions**, suggesting **no significant** cost differences among them.

MIDDLE FUNNEL METRICS ANALYSIS

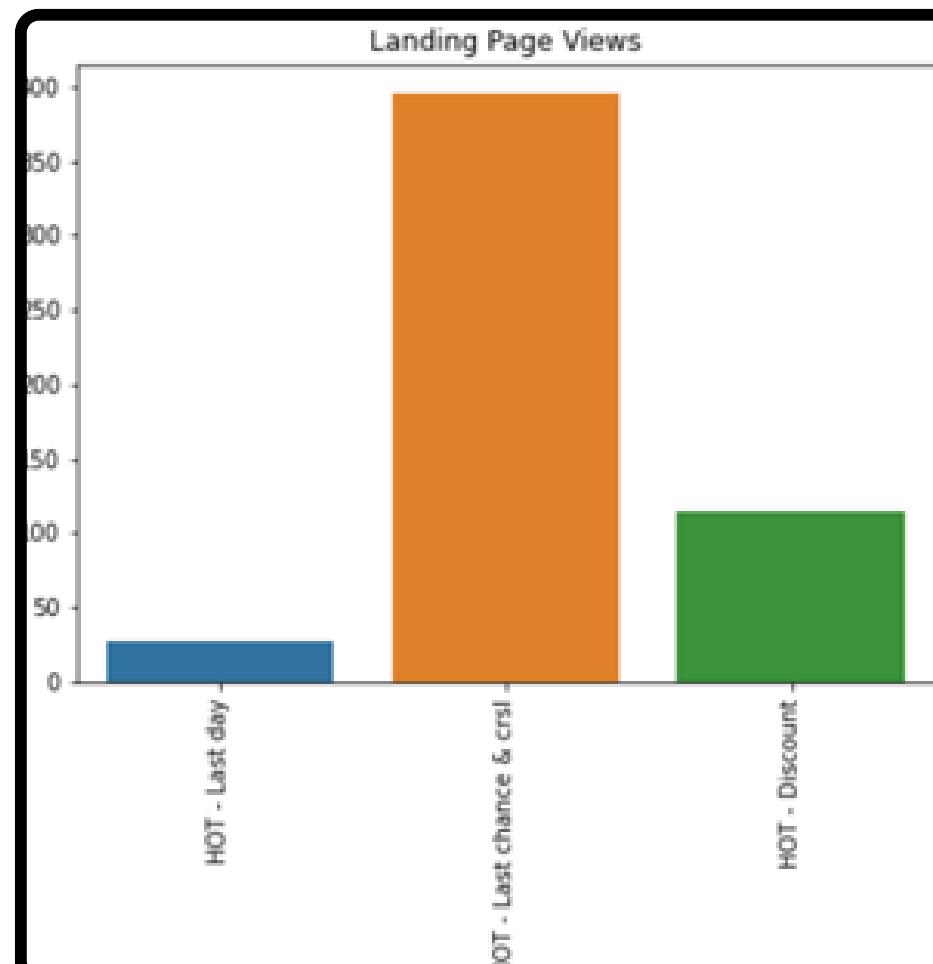
[HOT AD SET]

- **Middle Funnel Metrics**

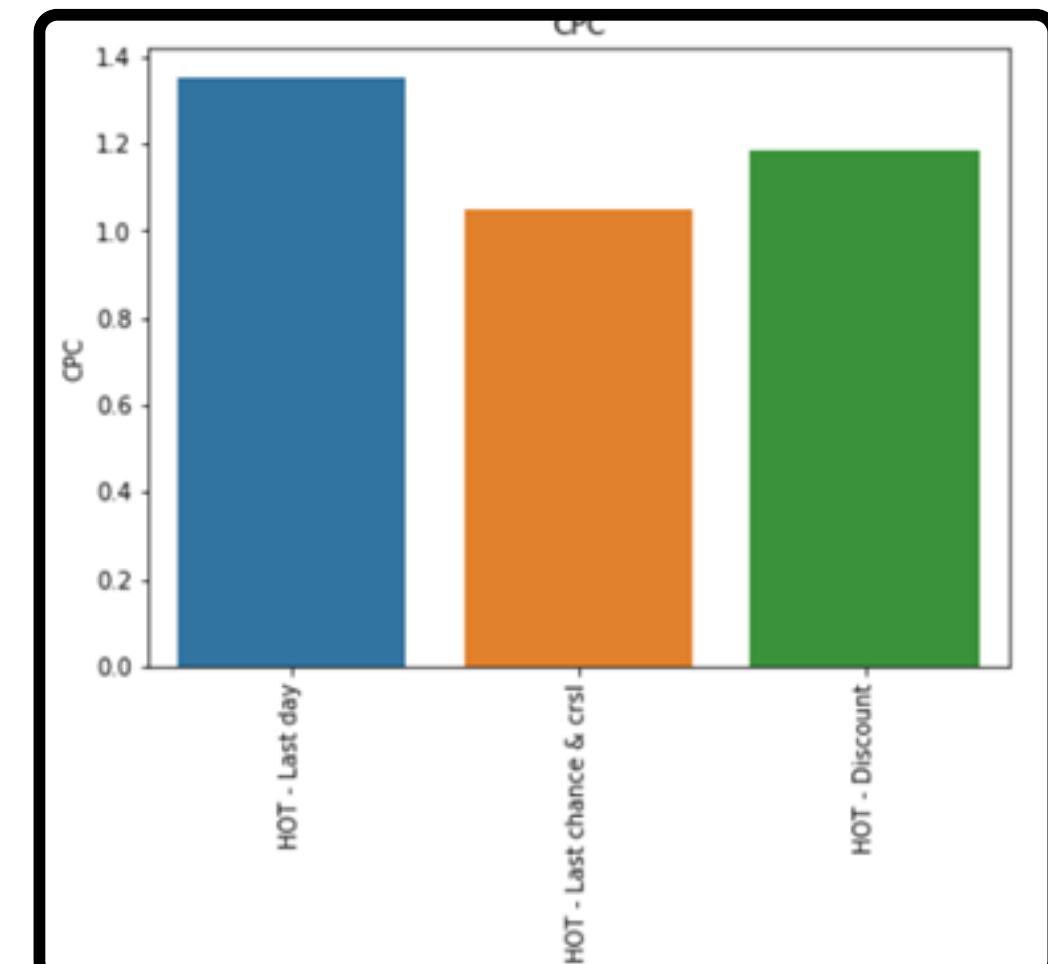
The ad set (**Last - Chance & Crsl**) shows **higher CTR** and **views** with **low CPC** which means **more engaging users**.



CTR



Landing Page Views



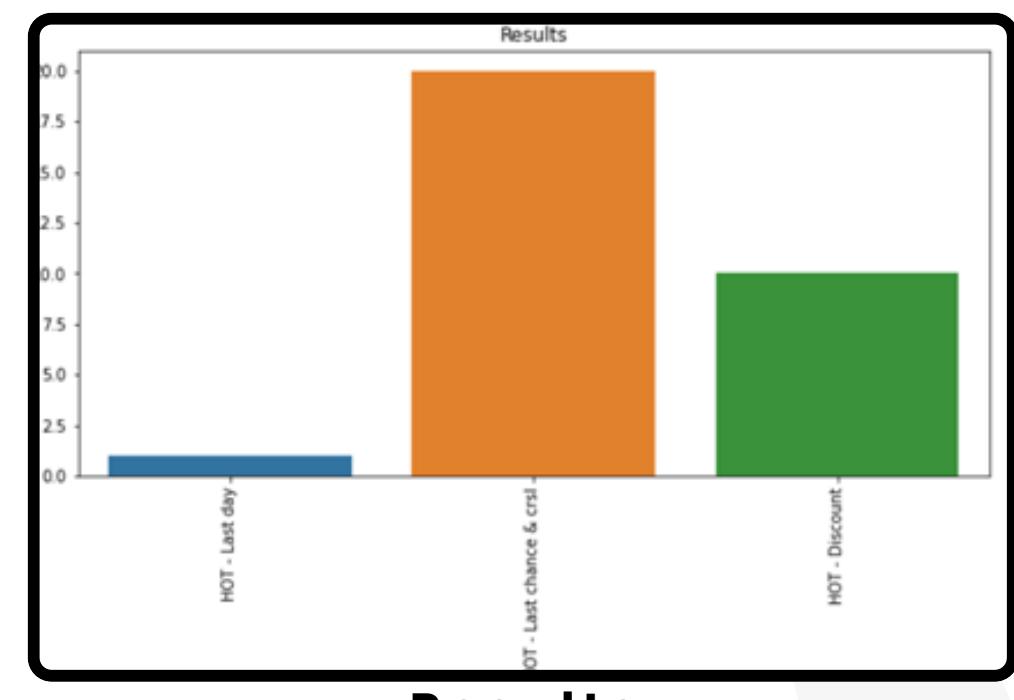
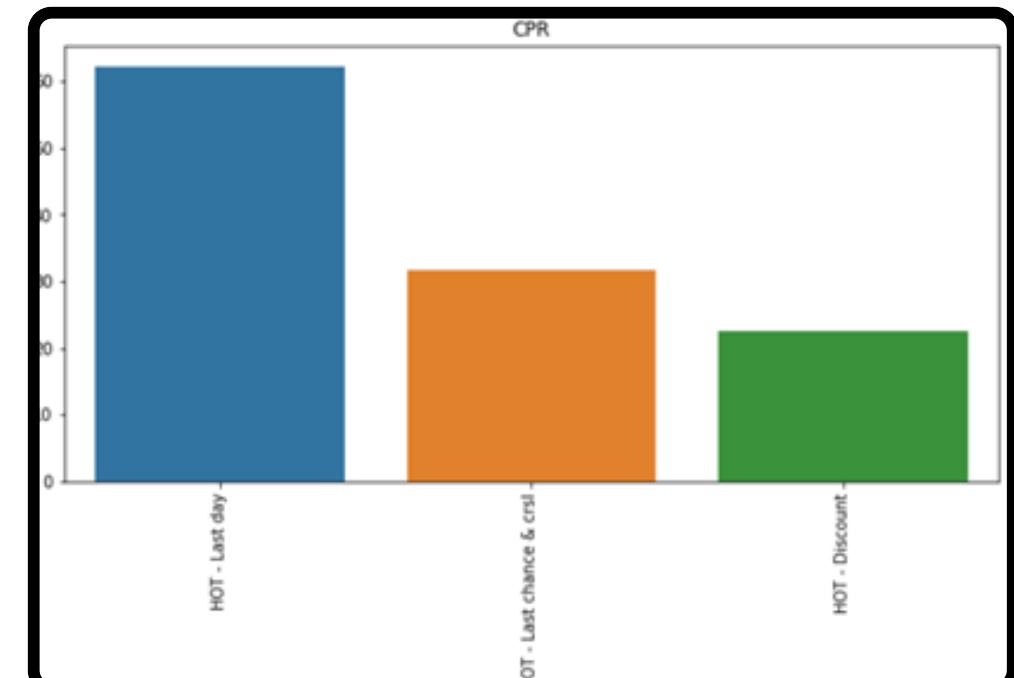
CPC

BOTTOM FUNNEL METRICS ANALYSIS

[HOT AD SET]

CPR & Results

- (Last - Chance & Crsl) and Discount Ad Sets:
 - **(Last - Chance & Crsl)** achieves **higher results** but has a **higher CPR** (Cost Per Result) at **31** Euro.
 - **Discount ad set** is **more cost-effective** with a **CPR** of **22** Euro, making it **cheaper** for obtaining **results**.
- Last Day Ad Set:
 - It performs poorly with **fewer results** and the **highest CPR**, indicating it might not be as effective in achieving desired outcomes compared to other Hot ad sets.

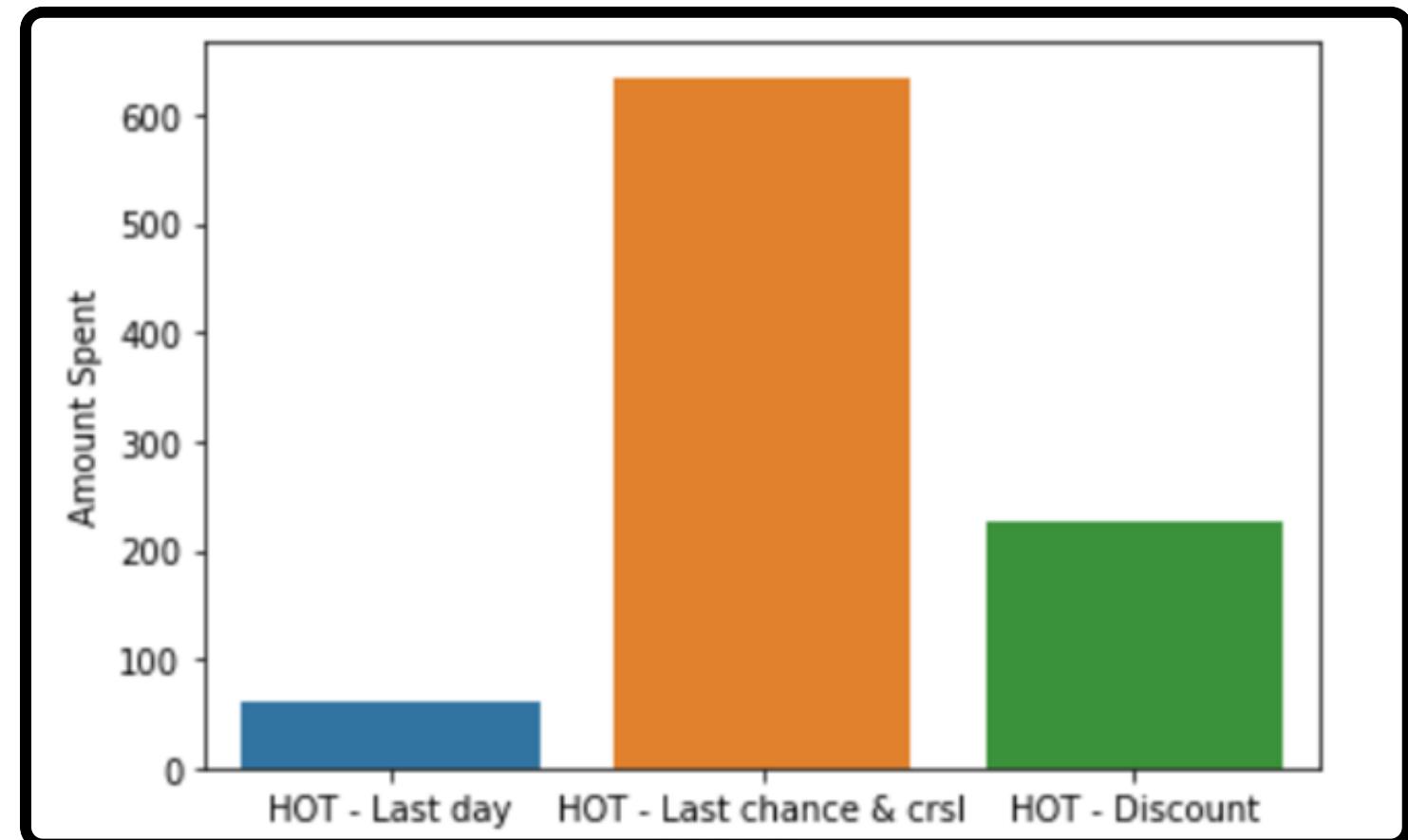


BOTTOM FUNNEL METRICS ANALYSIS

[HOT AD SET]

Ad Set Amount Spent

- The company spent around **600 euros** on Hot (**Last - Chance & Crsl**).
- (Last - Chance & Crsl) has a **higher** overall **cost** than Hot-Discount, which had an expenditure of around **210 euros**.
- Despite the **lower** spending, Hot-Discount is **more cost-effective**, with a **lower cost per result**.
- **Suggesting** it might be advisable to **allocate more budget** to this Hot-Discount Ad set for potentially better results at a lower cost per outcome.





THANK YOU

[Go back to Agenda Page](#)

PROJECT'S LINK:
[Click to Explore The Code](#)