Campaign Peformance Analysis

The goal of this analysis of Campaign Performance data is to evaluate how each marketing channel has performed over the given time periods.

Dataset Description

The dataset contains advertising metrics by marketing channel and week (e.g., Facebook, Google, Email, LinkedIn, Twitter). Fields include Week Start Date, Channel, Impressions, Clicks, Conversions, and Spend.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set(style='whitegrid')

data =
pd.read_csv('marketing_dummy_datasets/campaign_performance_data.csv')
data.head()
```

```
  Week Start Date     Channel  Impressions  Clicks  Conversions
Spend
0      2025-01-06    Facebook       171958    2914          101
4736.63
1      2025-01-06  Google Ads       257892    1892           61
754.42
2      2025-01-06       Email       162727    1628           51
2289.80
3      2025-01-06    LinkedIn       114820    2244          194
1483.23
4      2025-01-06     Twitter        55311    1099           76
1472.45
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 130 entries, 0 to 129
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Week Start Date  130 non-null    object
 1   Channel          130 non-null    object
 2   Impressions      130 non-null    int64
 3   Clicks           130 non-null    int64
 4   Conversions      130 non-null    int64
 5   Spend            130 non-null    float64
```

```
dtypes: float64(1), int64(3), object(2)
memory usage: 6.2+ KB
```

As we can see that there are no null values. First we normalize all the column names then convert data type of `Week Start Date` from object to datetime for monthly or seasonal trends.

```
data.columns = data.columns.str.lower().str.replace(' ', '_')

data['week_start_date'] = pd.to_datetime(data['week_start_date'])
data['month'] = data['week_start_date'].dt.to_period('M')

data.describe()
```

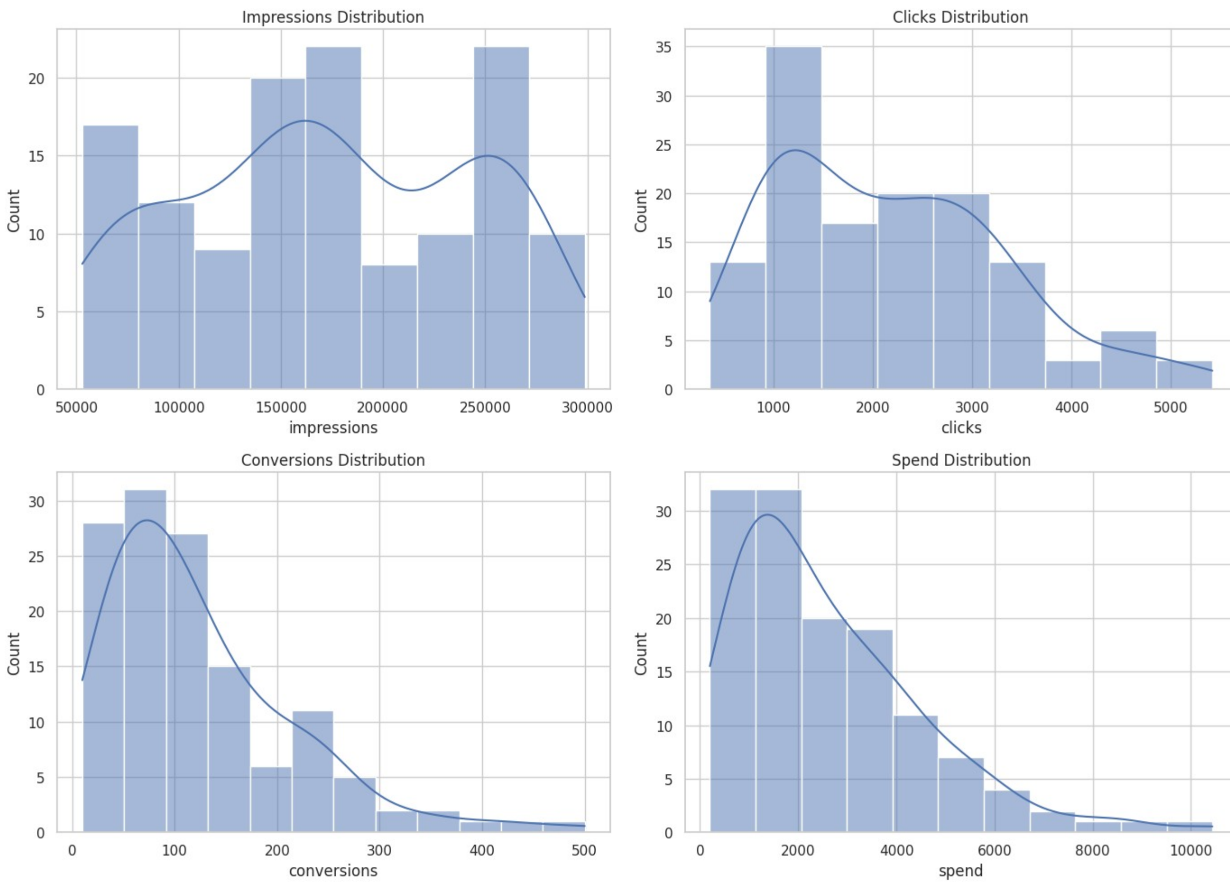
```
           week_start_date    impressions        clicks   conversions  \
count                  130      130.000000    130.000000    130.000000
mean   2025-04-03 12:00:00  172902.369231   2172.200000    124.246154
min    2025-01-06 00:00:00   52869.000000    362.000000     10.000000
25%    2025-02-17 00:00:00  117227.500000   1171.250000     59.000000
50%    2025-04-03 12:00:00  169677.000000   2045.500000     99.500000
75%    2025-05-19 00:00:00  243332.750000   2944.750000    165.750000
max    2025-06-30 00:00:00  298710.000000   5416.000000    500.000000
std                    NaN   70026.873807   1153.334205     91.546748

              spend
count    130.000000
mean    2613.892846
min      201.590000
25%     1137.032500
50%     2118.650000
75%     3644.142500
max    10436.350000
std     1919.734221
```

Metric	Observations
Impressions	Range: 52,869 → 298,710Mean: ~173k→ Wide range. Possible outliers on the high end (max ~300k).
Clicks	Range: 362 → 5,416Mean: ~2,172→ Large std dev (~1,153) indicates significant variation.
Conversions	Range: 10 → 500Mean: ~124→ Again, wide spread. Some weeks/channels might dominate.
Spend	Range: \201 → \10,436Mean: ~\2,614→ High spend outliers exist; budget skewed.

Lets check for outliers visually.

```
fig, axes = plt.subplots(2, 2, figsize=(14, 10))
sns.histplot(data['impressions'], ax=axes[0,0], kde=True)
axes[0,0].set_title('Impressions Distribution')
```

```
sns.histplot(data['clicks'], ax=axes[0,1], kde=True)
axes[0,1].set_title('Clicks Distribution')
sns.histplot(data['conversions'], ax=axes[1,0], kde=True)
axes[1,0].set_title('Conversions Distribution')
sns.histplot(data['spend'], ax=axes[1,1], kde=True)
axes[1,1].set_title('Spend Distribution')
plt.tight_layout()
```



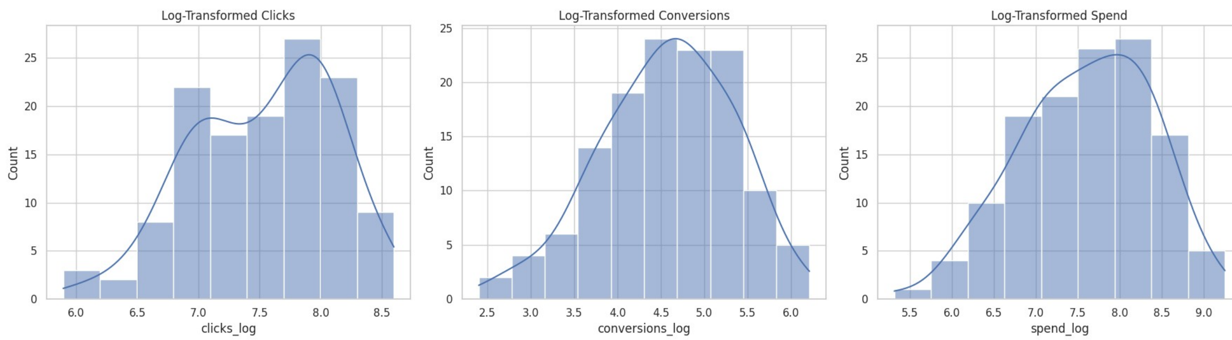
Distribution Observations

- **Impressions**: Appears multimodal or roughly uniform; does not need transformation.
- **Clicks, Conversions, Spend**: All show right-skewness, which can impact statistical modeling and machine learning.

We will apply log transformation to normalize the distributions and stabilize variance.

```
data['clicks_log'] = np.log1p(data['clicks'])        # log1p handles
0 safely
data['conversions_log'] = np.log1p(data['conversions'])
data['spend_log'] = np.log1p(data['spend'])

fig, axs = plt.subplots(1, 3, figsize=(18, 5))
```

```
sns.histplot(data['clicks_log'], kde=True, ax=axs[0])
axs[0].set_title('Log-Transformed Clicks')

sns.histplot(data['conversions_log'], kde=True, ax=axs[1])
axs[1].set_title('Log-Transformed Conversions')

sns.histplot(data['spend_log'], kde=True, ax=axs[2])
axs[2].set_title('Log-Transformed Spend')

plt.tight_layout()
plt.show()
```



Feature Engineering

```
## Performance Metrics
## Calculate Click-Through Rate (CTR), Conversion Rate, and Cost per
Conversion
data["click_rate"] = data["clicks_log"] / data["impressions"]
data["conversion_rate"] = data["conversions_log"] / data["clicks_log"]
data["cost_per_conversion"] = data["spend_log"] /
data["conversions_log"]

# --- Temporal Features ---
df['month'] = df['date'].dt.to_period('M')
data['week'] = data['week_start_date'].dt.isocalendar().week
data['day_of_week'] = data['week_start_date'].dt.day_name()
```

Analysis

Channel-Level Performance

Evaluate how each marketing channel performed based on:

```
- CTR (click-through rate)
- Conversion Rate
- Cost per Conversion
```

```
channel_summary = data.groupby("channel")[
    ["click_rate", "conversion_rate", "cost_per_conversion"]
].mean().sort_values("click_rate", ascending=False)

channel_summary.style.background_gradient(cmap="YlGnBu")
```

```
<pandas.io.formats.style.Styler at 0x7fe2e831e710>
```

Click-Through Rate (CTR):

```
- Twitter leads with the highest CTR, suggesting high engagement per
impression.
- Google Ads trails behind, possibly due to ad fatigue or lower
relevance.
```

Conversion Rate:

```
- All channels hover around ~0.60, but:
    - Facebook and LinkedIn slightly outperform others in converting
clicks to actions.
    - Google Ads has the lowest conversion rate, indicating weaker
post-click experiences.
```

Cost per Conversion

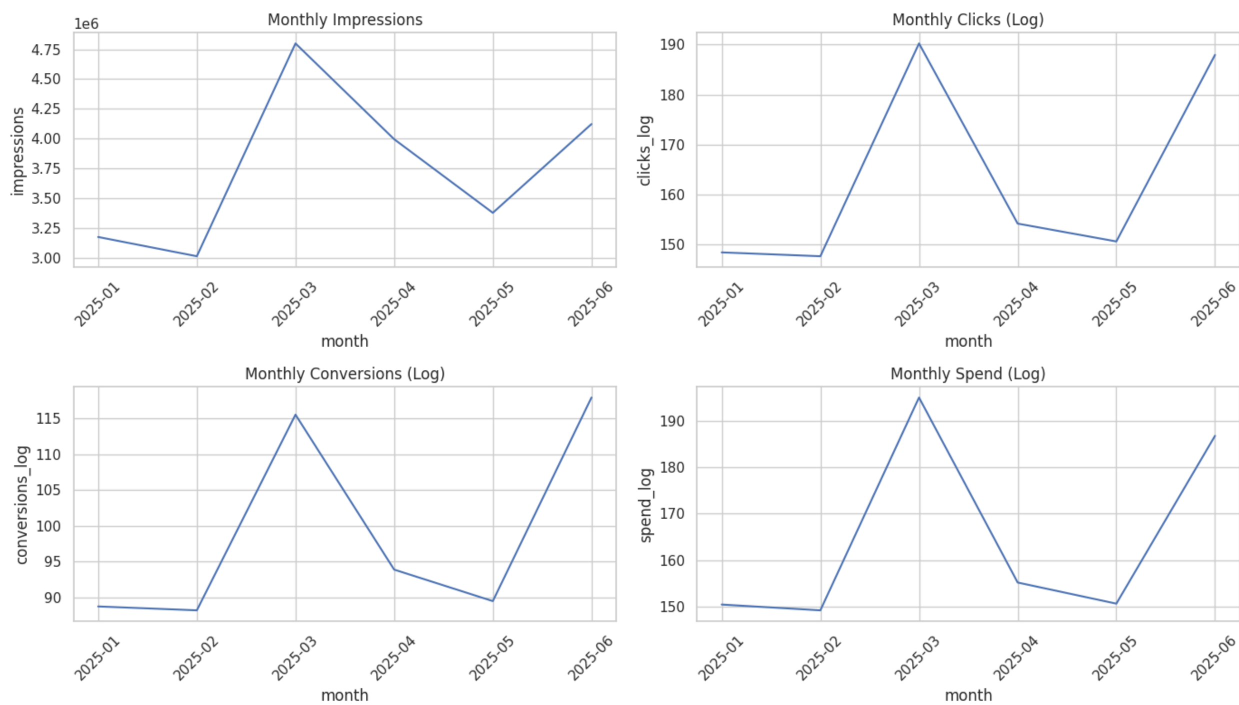
```
- Email has the lowest cost per conversion, suggesting it's the most
efficient channel.
- Google Ads again has the worst efficiency, with the highest spend
per conversion.
```

Monthly Trends

Analyze performance over time to identify seasonal patterns or campaign timing effects.

```
# Group by month
monthly_trends = data.groupby("month")[
    ["impressions", "clicks_log", "conversions_log", "spend_log"]
].sum().reset_index()

# Fix for plotting issue: convert Period to str or datetime
monthly_trends["month"] = monthly_trends["month"].astype(str)

# Plotting
import matplotlib.pyplot as plt
import seaborn as sns

fig, axs = plt.subplots(2, 2, figsize=(14, 8))
sns.lineplot(data=monthly_trends, x="month", y="impressions",
ax=axs[0, 0])
```

```
sns.lineplot(data=monthly_trends, x="month", y="clicks_log", ax=axs[0, 1])
sns.lineplot(data=monthly_trends, x="month", y="conversions_log", ax=axs[1, 0])
sns.lineplot(data=monthly_trends, x="month", y="spend_log", ax=axs[1, 1])

axs[0, 0].set_title("Monthly Impressions")
axs[0, 1].set_title("Monthly Clicks (Log)")
axs[1, 0].set_title("Monthly Conversions (Log)")
axs[1, 1].set_title("Monthly Spend (Log)")

# Rotate x-axis labels for better readability
for ax in axs.flat:
    ax.tick_params(axis='x', rotation=45)

plt.tight_layout()
plt.show()
```

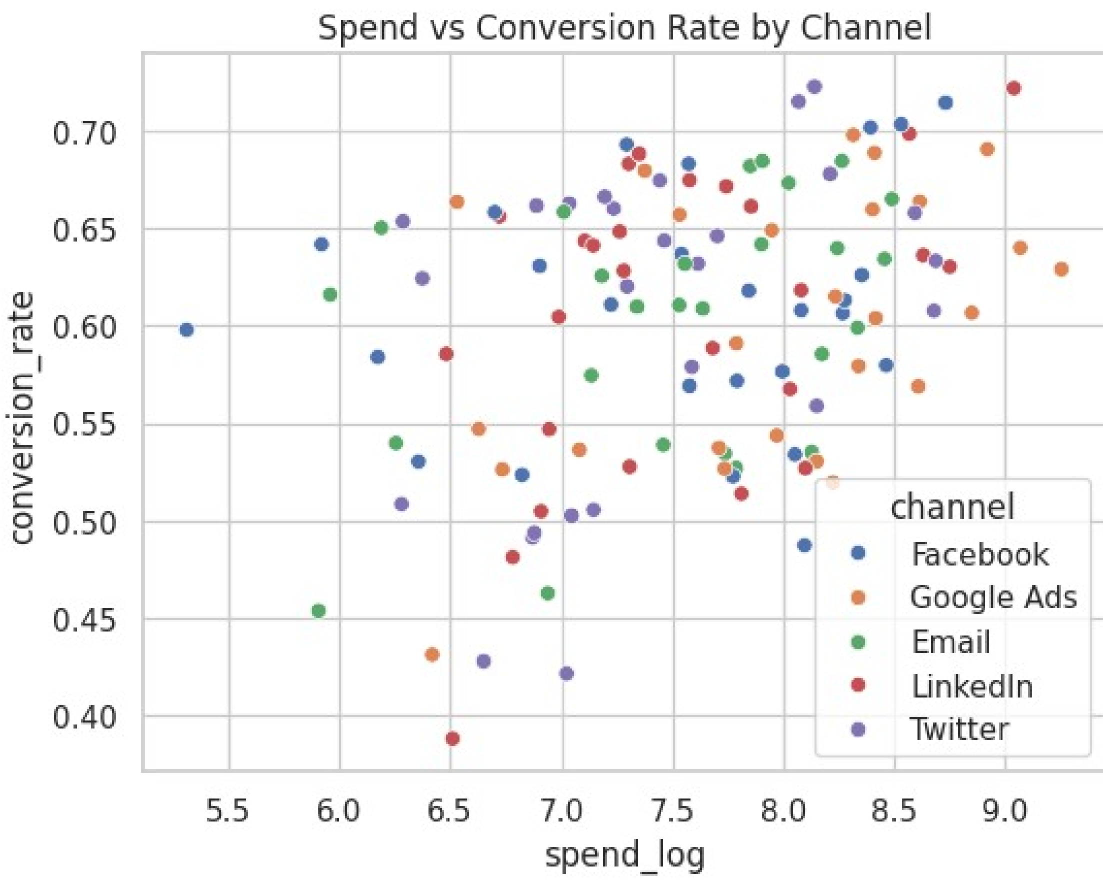


Month	Key Takeaway
March	High spend, high impressions, clicks, and conversions — likely a major campaign with broad reach.
June	Lower impressions than March, but **best conversion efficiency** — possibly due to better targeting or offer quality.
Feb/May	Lower across all metrics — potential off-season or underperforming campaigns.

Spend vs Conversion Rate by Channel — With Efficiency Zones

This chart visualizes how efficiently each marketing channel converts leads into customers based on spend.

```
sns.scatterplot(data=data, x="spend_log", y="conversion_rate",
hue="channel")
plt.title("Spend vs Conversion Rate by Channel")
plt.show()
```



Trends:

```
- No strong linear correlation between spend and conversion rate—more
spend ≠ better performance.
- Channels like Twitter, LinkedIn, and Email show higher efficiency in
converting users.
- Google Ads and Facebook show potential, but may be less cost-
effective without fine-tuning.
```

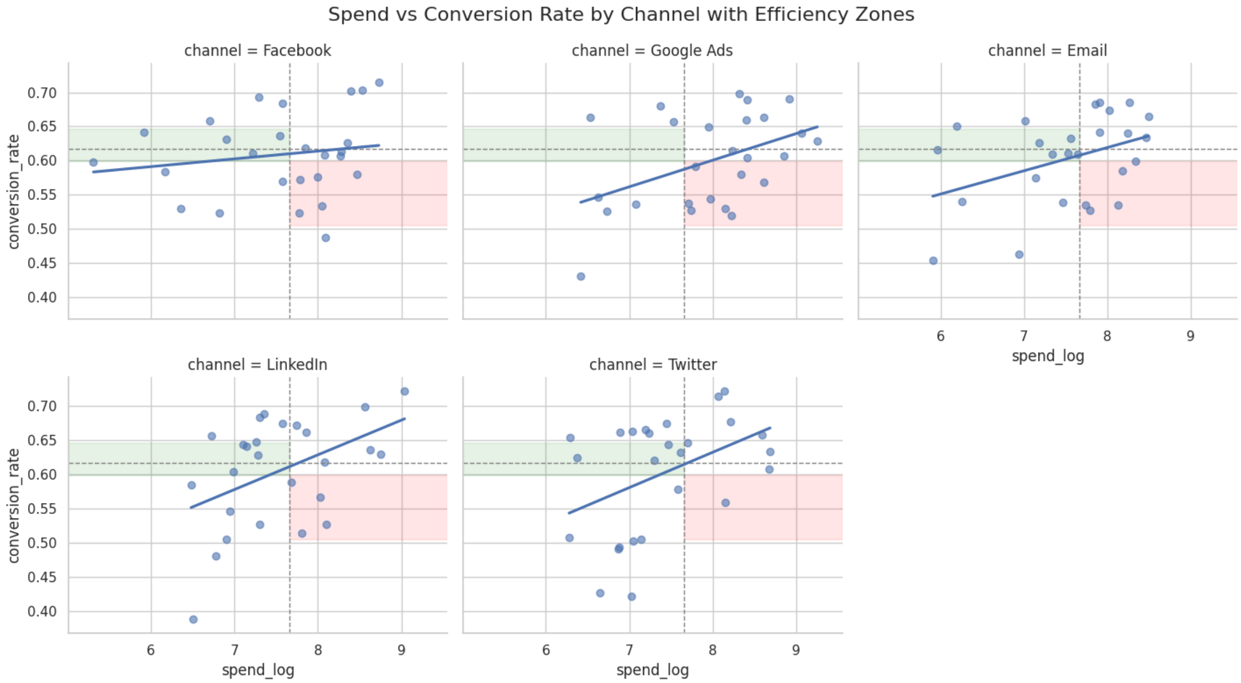
Suggestions:

```
- Optimize budget allocation toward high-efficiency channels: Twitter, LinkedIn, and Email.
- Reassess Facebook & Google Ads campaigns—analyze segments, creatives, and targeting strategies.
- A/B test ad creatives or targeting options for underperforming high-spend campaigns.
```

Lets check this for individual companies.

```python
# Calculate global medians
spend_median = data["spend_log"].median()
conversion_median = data["conversion_rate"].median()

 # X/Y limits from actual data (for tight bounding)
spend_min = data["spend_log"].min()
spend_max = data["spend_log"].max()
conv_min = data["conversion_rate"].min()
conv_max = data["conversion_rate"].max()

# Set up FacetGrid
g = sns.FacetGrid(data, col="channel", col_wrap=3, height=4, aspect=1.2)

# Define plot function with shaded zones
def plot_with_zones(data, color, **kwargs):
    ax = plt.gca()

    # Expand just a little for breathing room
    ax.set_xlim(spend_min - 0.3, spend_max + 0.3)
    ax.set_ylim(conv_min - 0.02, conv_max + 0.02)


    # Shaded quadrants
    ax.axvspan(xmin=ax.get_xlim()[0], xmax=spend_median, ymin=conversion_median, ymax=ax.get_ylim()[1], color='green', alpha=0.1)
    ax.axvspan(xmin=spend_median, xmax=ax.get_xlim()[1], ymin=ax.get_ylim()[0], ymax=conversion_median, color='red', alpha=0.1)

    # Median lines
    ax.axvline(spend_median, color='gray', linestyle='--', linewidth=1)
    ax.axhline(conversion_median, color='gray', linestyle='--', linewidth=1)

    # Scatter + trend
    sns.regplot(data=data, x="spend_log", y="conversion_rate", scatter=True, ci=None, line_kws={"color": color}, scatter_kws={"alpha": 0.6}, ax=ax)
```

```python
# Map plotting function to grid
g.map_dataframe(plot_with_zones)

g.fig.subplots_adjust(top=0.9)
g.fig.suptitle("Spend vs Conversion Rate by Channel with Efficiency Zones", fontsize=16)
plt.show()
```



This analysis maps out the efficiency of our spend across channels. The green zone represents ideal performance — high conversion for low spend. Red indicates inefficiencies. With this, we can double down on what works (like Email), cautiously scale what shows promise (Google Ads), and reevaluate underperformers (Twitter/LinkedIn) to optimize ROI.

Key Insights by Channel:

Facebook

```
- Slight positive correlation between spend and conversion.
- Campaigns mostly near the median — underutilized efficiency potential.
- A few efficient (green zone) campaigns, but not dominant.
```

Google Ads

```
- Clear positive correlation — higher spend improves conversion rate.
- Red zone shows some inefficiencies at high spend.
- Scaling possible but should be monitored for diminishing returns.
```

Email

```
- Tight clustering of data points.
- Many campaigns in the green zone – highly efficient.
- Recommended to continue or slightly increase spend.
```

LinkedIn

```
- Strong positive trend, but many points fall in the red zone.
- May become inefficient at higher spend.
- Use for targeted campaigns rather than scale.
```

Twitter

```
- Moderate positive trend but wide spread in performance.
- Appears inconsistent – both efficient and inefficient campaigns.
- Needs improved targeting to reduce spend wastage.
```

Strategic Recommendations:

Channel	Recommendation
Email	Highly efficient — scale investment gradually.
Google Ads	Effective at scale — monitor ROI to prevent inefficiency.
Facebook	Explore optimization strategies — potential for improvement.
LinkedIn	Limit budget — invest in high-intent segments only.
Twitter	Refine audience targeting to improve consistency.

Conclusion

This analysis provided a data-driven view of how spend influences conversion rates across key marketing channels.

Key Takeaways:

- **Email** is the most efficient channel with consistently high conversion and low spend — a prime candidate for further scaling.
- **Google Ads** shows a strong return on higher spend, but requires monitoring for diminishing returns beyond a certain threshold.
- **Facebook** has stable performance but underutilized efficiency. There's room to optimize without increasing budget drastically.
- **LinkedIn** and **Twitter** exhibit lower efficiency at higher spend levels — suggesting a need for audience refinement or budget reallocation.

Strategic Action:

We should adopt a **channel-specific spend strategy**:

- **Scale** proven efficient channels (Email, Google Ads).
- **Optimize** and experiment with mid-performance channels (Facebook).
- **Reduce or redirect** spend from underperforming zones (LinkedIn, Twitter) unless new targeting strategies are tested.

This approach ensures we're maximizing marketing ROI by aligning spend with conversion efficiency across channels.