In this project, I analyze Adsphere (a fictional ad platform) data to explore two research questions: (1) Do advertisers with the most campaigns/ads generate the most revenue? (2) How do ad presentation choices (formats, CTAs) differ across platforms and placements? The analysis uses SQL and Python (Seaborn/Matplotlib) to explore patterns and test relationships

In [333…

```
!pip -q install mysql-connector-python SQLAlchemy pandas matplotlib

import sys, sqlalchemy, pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt

print("Python:", sys.version.split()[0])
print("SQLAlchemy:", sqlalchemy.__version__)
print("pandas:", pd.__version__)
```

```
Python: 3.11.5
SQLAlchemy: 1.4.39
pandas: 2.0.3
```

In [315…

```
# --- RDS Connection Settings ---
DB_HOST = "127.0.0.1"
DB_PORT = 3306
DB_NAME = "adsphere"
```

In [78]:

```
from getpass import getpass
DB_USER = input("MySQL username: ").strip()
DB_PASS = getpass("MySQL password: ").strip()
```

```
MySQL username: matt
MySQL password: ········
```

In [336…

```
from sqlalchemy import create_engine, text

# 1) Connect to server (no DB) to verify credentials and list schemas
server_engine = create_engine(
    f"mysql+mysqlconnector://{DB_USER}:{DB_PASS}@{DB_HOST}:{DB_PORT}",
    pool_pre_ping=True,
)

with server_engine.connect() as conn:
    print("Ping:", conn.execute(text("SELECT 1")).scalar_one())
    dbs = pd.read_sql_query(text("SHOW DATABASES"), conn)
    # display(dbs)

    # 2) Ensure target DB exists; create it if needed (comment out if you don'
with server_engine.connect() as conn:
    conn.execute(text(f"CREATE DATABASE IF NOT EXISTS `{DB_NAME}` CHARACTER SE
    print(f"Verified database `{DB_NAME}`")

# 3) Connect directly to the target DB (still no SSL)
engine = create_engine(
    f"mysql+mysqlconnector://{DB_USER}:{DB_PASS}@{DB_HOST}:{DB_PORT}/{DB_NAME}"
    pool_pre_ping=True,
)
```

```python
with engine.connect() as conn:
    print("SELECT 1 →", conn.execute(text("SELECT 1")).scalar_one())
    print("Current DB:", conn.execute(text("SELECT DATABASE()")).scalar_one())

    print("\nTables:")
    try:
        display(pd.read_sql_query(text("SHOW TABLES"), conn))
    except Exception as e:
        print("SHOW TABLES failed:", e)

    for t in ("ad", "campaign", "advertiser", "v_ad_performance", "platform"):
        try:
            print(f"\nDESCRIBE {t}:")
            display(pd.read_sql_query(text(f"DESCRIBE `{t}`"), conn))
        except Exception:
            pass
```

```
Ping: 1
Verified database `adsphere`
SELECT 1 → 1
Current DB: adsphere

Tables:
```

	Tables_in_adsphere
0	ad
1	ad_event
2	advertiser
3	campaign
4	country
5	device_type
6	event_type
7	placement
8	platform
9	user_profile
10	v_ad_performance

```
DESCRIBE ad:
```

	Field	Type	Null	Key	Default	Extra
0	ad_id	int	NO	PRI	None	auto_increment
1	campaign_id	int	NO	MUL	None	
2	platform_id	int	NO	MUL	None	
3	placement_id	int	NO	MUL	None	
4	name	varchar(160)	NO		None	
5	headline	varchar(180)	NO		None	
6	ad_text	text	NO		None	
7	cta	enum('Learn More','Shop Now','Sign Up','Downlo...	NO		None	
8	bid_cents	int	NO		None	
9	creative_format	enum('image','video','carousel','text')	NO		None	
10	url	varchar(255)	YES		None	
11	created_at	datetime	NO		None	
12	status	enum('active','paused','archived')	NO		active	

```
DESCRIBE campaign:
```

	Field	Type	Null	Key	Default	Extra
0	campaign_id	int	NO	PRI	None	auto_increment
1	advertiser_id	int	NO	MUL	None	
2	name	varchar(160)	NO		None	
3	objective	enum('reach','traffic','video_views','conversi...	NO		None	
4	daily_budget	decimal(10,2)	NO		None	
5	start_date	date	NO		None	
6	end_date	date	YES		None	
7	status	enum('active','paused','completed')	NO		active	

```
DESCRIBE advertiser:
```

	Field	Type	Null	Key	Default	Extra
0	advertiser_id	int	NO	PRI	None	auto_increment
1	name	varchar(128)	NO	UNI	None	
2	website	varchar(255)	YES		None	
3	country_id	int	YES	MUL	None	
4	industry	varchar(64)	YES		None	

```
DESCRIBE v_ad_performance:
```

	Field	Type	Null	Key	Default	Extra
0	ad_id	int	NO		0	
1	ad_name	varchar(160)	NO		None	
2	platform	varchar(64)	NO		None	
3	placement	varchar(64)	NO		None	
4	campaign_id	int	NO		0	
5	campaign_name	varchar(160)	NO		None	
6	advertiser_name	varchar(128)	NO		None	
7	impressions	decimal(23,0)	YES		None	
8	clicks	decimal(23,0)	YES		None	
9	purchases	decimal(23,0)	YES		None	
10	total_cost	decimal(30,4)	YES		None	
11	total_revenue	decimal(30,4)	YES		None	

```
DESCRIBE platform:
```

	Field	Type	Null	Key	Default	Extra
0	platform_id	int	NO	PRI	None	auto_increment
1	name	varchar(64)	NO	UNI	None	

Research Question 1: Are companies with the most active campaigns and ads also the top performers? Specifically, is there a correlation between ad volume and performance, or does having more ads not necessarily lead to higher results?

Step 1: Identify which advertisers maintain the highest number of active campaigns.

In [317…

```
sql = """
SELECT a.name "Advertiser", a.industry "Industry", COUNT(c.campaign_id) "Numbe
FROM advertiser a
INNER JOIN campaign c
ON a.advertiser_id = c.advertiser_id
WHERE c.status LIKE 'active'
GROUP BY Advertiser
ORDER BY count(c.campaign_id) DESC
LIMIT 20
"""
with engine.connect() as conn:
    df_1 = pd.read_sql_query(text(sql), conn)

df_1
```

Out[317]:

	Advertiser	Industry	Number of Campaigns
0	Quantum Furniture	finance	4
1	Rocket Fitness 02	travel	3
2	Lunar Foods	cpg	3
3	Magnet Electronics 02	finance	3
4	Golden Books	gaming	2
5	Urban Market	saas	2
6	Rocket Outfitters	health	2
7	Quantum Outfitters	ecommerce	2
8	Silver Tools 02	ecommerce	2
9	Silver Furniture	travel	2
10	Urban Market 02	retail	2
11	Phoenix Studios	saas	2
12	Apex Toys	education	2
13	Quantum Foods	education	2
14	Apex Auto 02	ecommerce	2
15	Green Games	health	2
16	Rocket Studios	health	2
17	Blue Cloud	health	2
18	Rocket Electronics	education	2
19	Rapid Bikes	health	2

Next, I want to analyze advertisers at a more granular level by looking at the number of ads they run and the average number of ads per campaign. I focus only on active campaigns and ads to keep the analysis current. An INNER JOIN ensures we only include advertisers that actually have campaigns, while a LEFT JOIN on ads prevents inflating the "Avg Active Ads per Campaign" (since some advertisers may have campaigns without active ads).

In [318…

```
sql = """
SELECT
a1.name Advertiser, a1.industry Industry, COUNT(DISTINCT(c.campaign_id)) "Numbe
COUNT(a2.ad_id) 'Number of Ads',
ROUND(COUNT(a2.ad_id) * 1.0 / NULLIF(COUNT(DISTINCT c.campaign_id), 0),2) 'Avg
FROM advertiser a1
INNER JOIN campaign c
ON c.advertiser_id = a1.advertiser_id
LEFT JOIN ad a2
ON a2.campaign_id = c.campaign_id
WHERE a2.status = 'active' AND c.status = 'active'
GROUP BY Advertiser
ORDER BY COUNT(a2.ad_id) DESC, COUNT(DISTINCT(c.campaign_id)) DESC
LIMIT 20;
"""
```

```
with engine.connect() as conn:
    df_2 = pd.read_sql_query(text(sql), conn)

df_2
```

Out[318]:

	Advertiser	Industry	Number of Campaigns	Number of Ads	Avg Active Ads per Campaign
0	Quantum Furniture	finance	4	42	10.50
1	Rocket Fitness 02	travel	3	38	12.67
2	Magnet Electronics 02	finance	3	36	12.00
3	Blue Cloud	health	2	34	17.00
4	Lunar Foods	cpg	3	31	10.33
5	Quantum Outfitters	ecommerce	2	31	15.50
6	Bright Skincare	travel	2	30	15.00
7	Rocket Electronics	education	2	27	13.50
8	Green Games	health	2	25	12.50
9	Golden Auto	education	2	25	12.50
10	Urban Market	saas	2	24	12.00
11	Rocket Studios	health	2	23	11.50
12	Apex Toys	education	2	23	11.50
13	Rocket Outfitters	health	2	23	11.50
14	Urban Market 02	retail	2	21	10.50
15	Silver Market	retail	2	20	10.00
16	Phoenix Studios	saas	2	20	10.00
17	Apex Auto 02	ecommerce	2	19	9.50
18	Echo Tools	health	2	19	9.50
19	Golden Books	gaming	2	19	9.50

From the initial results, advertisers like Quantum Furniture and Rock Fitness 02 lead in active campaigns and ads, with Lunar Foods and Magnet Electronics 02 also appearing in the top five.

Next, I shift focus to revenue under the same "active only" criteria. This is a good opportunity to use a CTE: it lets me identify the top-grossing advertisers while maintaining the filtering logic established earlier. I also include the count of distinct Ad IDs as a preview of whether ad volume might correlate with revenue performance.

In [319…

```
sql = """
WITH active_ads AS (
SELECT a2.ad_id
FROM ad a2
```

```
JOIN campaign c
ON c.campaign_id = a2.campaign_id
AND c.status = 'active'
WHERE a2.status = 'active'
)
SELECT
v.advertiser_name,
COUNT(DISTINCT v.ad_id) active_ads,
SUM(v.impressions) impressions,
SUM(v.clicks) clicks,
SUM(v.total_revenue) total_revenue
FROM v_ad_performance v
JOIN active_ads aa
ON aa.ad_id = v.ad_id
GROUP BY v.advertiser_name
ORDER BY total_revenue DESC
LIMIT 20;
"""
with engine.connect() as conn:
    df_3 = pd.read_sql_query(text(sql), conn)

df_3
```

Out[319]:

	advertiser_name	active_ads	impressions	clicks	total_revenue
0	Rocket Fitness 02	38	82.0	30.0	694.08
1	Urban Market	24	62.0	25.0	586.28
2	Apex Toys	23	62.0	15.0	454.02
3	Apex Electronics	9	28.0	5.0	414.06
4	Echo Tools	19	44.0	20.0	309.76
5	Apex Auto	16	32.0	16.0	303.93
6	Bright Music	16	37.0	10.0	274.58
7	Golden Books	19	48.0	10.0	262.99
8	Nova Toys	14	35.0	20.0	255.32
9	Vertex Books	9	21.0	7.0	249.65
10	Quantum Furniture	42	120.0	36.0	211.92
11	Summit Outfitters	12	28.0	12.0	202.33
12	Prime Travel	10	36.0	5.0	197.67
13	Rocket Fitness	12	18.0	12.0	180.01
14	Polar Bikes	12	35.0	7.0	179.34
15	Silver Foods	7	17.0	6.0	176.83
16	Blue Cloud	34	73.0	32.0	173.41
17	Lunar Outfitters	11	31.0	8.0	166.61
18	Silver Tools	10	33.0	9.0	160.03
19	Apex Auto 02	19	50.0	17.0	159.10

The results highlight recurring top advertisers, with Rocket Fitness 02 and Quantum Furniture consistently appearing near the top. Other strong performers include Lunar Foods and Magnet Electronics 02. This reinforces the pattern that certain advertisers dominate across both campaign activity and revenue.

Now it's time to place campaign volume and revenue performance side by side. Using another CTE allows both measures to be aligned and compared within a single query.

In [320…

```
sql = """
WITH top_volume AS (
SELECT
a1.name AS advertiser_name, a1.industry AS industry,
COUNT(DISTINCT c.campaign_id) AS active_campaigns,
COUNT(a2.ad_id) AS active_ads,
ROUND(COUNT(a2.ad_id) * 1.0 / NULLIF(COUNT(DISTINCT c.campaign_id), 0),2) AS a
FROM advertiser a1
INNER JOIN campaign c
ON c.advertiser_id = a1.advertiser_id
AND c.status = 'active'
LEFT JOIN ad a2
ON a2.campaign_id = c.campaign_id
AND a2.status = 'active'
GROUP BY a1.name, a1.industry
),

active_ads AS (
SELECT a2.ad_id, c.advertiser_id
FROM ad a2
JOIN campaign c
ON c.campaign_id = a2.campaign_id
AND c.status = 'active'
WHERE a2.status = 'active'
),

top_perf AS (
SELECT
v.advertiser_name,
COUNT(DISTINCT v.ad_id) AS active_ads,
SUM(v.impressions) AS impressions,
SUM(v.clicks) AS clicks,
SUM(v.total_revenue) AS total_revenue
FROM v_ad_performance v
JOIN active_ads aa
ON aa.ad_id = v.ad_id
GROUP BY v.advertiser_name
)

SELECT
v.advertiser_name,
v.active_ads,
v.active_campaigns,
p.total_revenue,
p.impressions,
p.clicks
FROM top_volume v
INNER JOIN top_perf p
ON p.advertiser_name = v.advertiser_name
```

```
ORDER BY p.total_revenue DESC
LIMIT 20;
"""
with engine.connect() as conn:
    df_4 = pd.read_sql_query(text(sql), conn)

df_4
```

Out[320]:

	advertiser_name	active_ads	active_campaigns	total_revenue	impressions	clicks
0	Rocket Fitness 02	38	3	694.08	82.0	30.0
1	Urban Market	24	2	586.28	62.0	25.0
2	Apex Toys	23	2	454.02	62.0	15.0
3	Apex Electronics	9	1	414.06	28.0	5.0
4	Echo Tools	19	2	309.76	44.0	20.0
5	Apex Auto	16	1	303.93	32.0	16.0
6	Bright Music	16	1	274.58	37.0	10.0
7	Golden Books	19	2	262.99	48.0	10.0
8	Nova Toys	14	1	255.32	35.0	20.0
9	Vertex Books	9	1	249.65	21.0	7.0
10	Quantum Furniture	42	4	211.92	120.0	36.0
11	Summit Outfitters	12	1	202.33	28.0	12.0
12	Prime Travel	10	1	197.67	36.0	5.0
13	Rocket Fitness	12	1	180.01	18.0	12.0
14	Polar Bikes	12	1	179.34	35.0	7.0
15	Silver Foods	7	1	176.83	17.0	6.0
16	Blue Cloud	34	2	173.41	73.0	32.0
17	Lunar Outfitters	11	1	166.61	31.0	8.0
18	Silver Tools	10	1	160.03	33.0	9.0
19	Apex Auto 02	19	2	159.10	50.0	17.0

This comparison helps identify which advertisers are strong in both campaign activity and revenue. To formally test correlation between ad volume and performance, I make slight adjustments to the query and then visualize the relationship using Seaborn and Matplotlib.

ROAS (Return on Ad Spend) is included as a performance metric in this query. Since the goal is visualization, no ordering is applied in the SQL so that results can be plotted directly.

In [322…

```
sql = """
WITH active_ads AS (
SELECT a2.ad_id, c.advertiser_id
FROM ad a2
JOIN campaign c
ON c.campaign_id = a2.campaign_id
AND c.status = 'active'
```

```
WHERE a2.status = 'active'
),

top_volume AS (
SELECT a1.advertiser_id,
COUNT(DISTINCT c.campaign_id) active_campaigns,
COUNT(DISTINCT a2.ad_id) active_ads
FROM advertiser a1
JOIN campaign c
ON c.advertiser_id = a1.advertiser_id
AND c.status = 'active'
LEFT JOIN ad a2
ON a2.campaign_id = c.campaign_id
AND a2.status = 'active'
GROUP BY a1.advertiser_id
),

top_perf AS (
SELECT ca.advertiser_id,
SUM(v.impressions) impressions,
SUM(v.clicks) clicks,
SUM(v.total_cost) total_cost,
SUM(v.total_revenue) total_revenue,
CASE WHEN SUM(v.total_cost) > 0 THEN SUM(v.total_revenue)/SUM(v.total_cost) END
FROM active_ads ca
JOIN v_ad_performance v
ON v.ad_id = ca.ad_id
GROUP BY ca.advertiser_id
)

SELECT a.advertiser_id, a.name advertiser_name,
top_volume.active_campaigns, top_volume.active_ads,
top_perf.impressions, top_perf.clicks,
top_perf.total_cost, top_perf.total_revenue, top_perf.ROAS
FROM advertiser a
JOIN top_volume
ON a.advertiser_id = top_volume.advertiser_id
JOIN top_perf
ON a.advertiser_id = top_perf.advertiser_id;
"""
with engine.connect() as conn:
    df_5 = pd.read_sql_query(text(sql), conn)

df_5
```

Out[322]:

	advertiser_id	advertiser_name	active_campaigns	active_ads	impressions	clicks	total_c
0	2	Urban Market	2	24	62.0	25.0	31.9
1	3	Silver Tools	1	10	33.0	9.0	9.8
2	4	Bright Music	1	16	37.0	10.0	13.5
3	5	Lunar Toys	1	14	41.0	6.0	8.2
4	6	Lunar Foods	3	31	65.0	29.0	29.0
...	...	...	...	...	...	...	
57	112	Phoenix Studios	2	20	56.0	14.0	13.6
58	115	Prime Travel 02	1	7	19.0	5.0	3.2
59	116	Nova Toys	1	14	35.0	20.0	17.0
60	117	Green Games	2	25	72.0	24.0	24.3
61	118	Summit Music	1	5	8.0	4.0	4.2

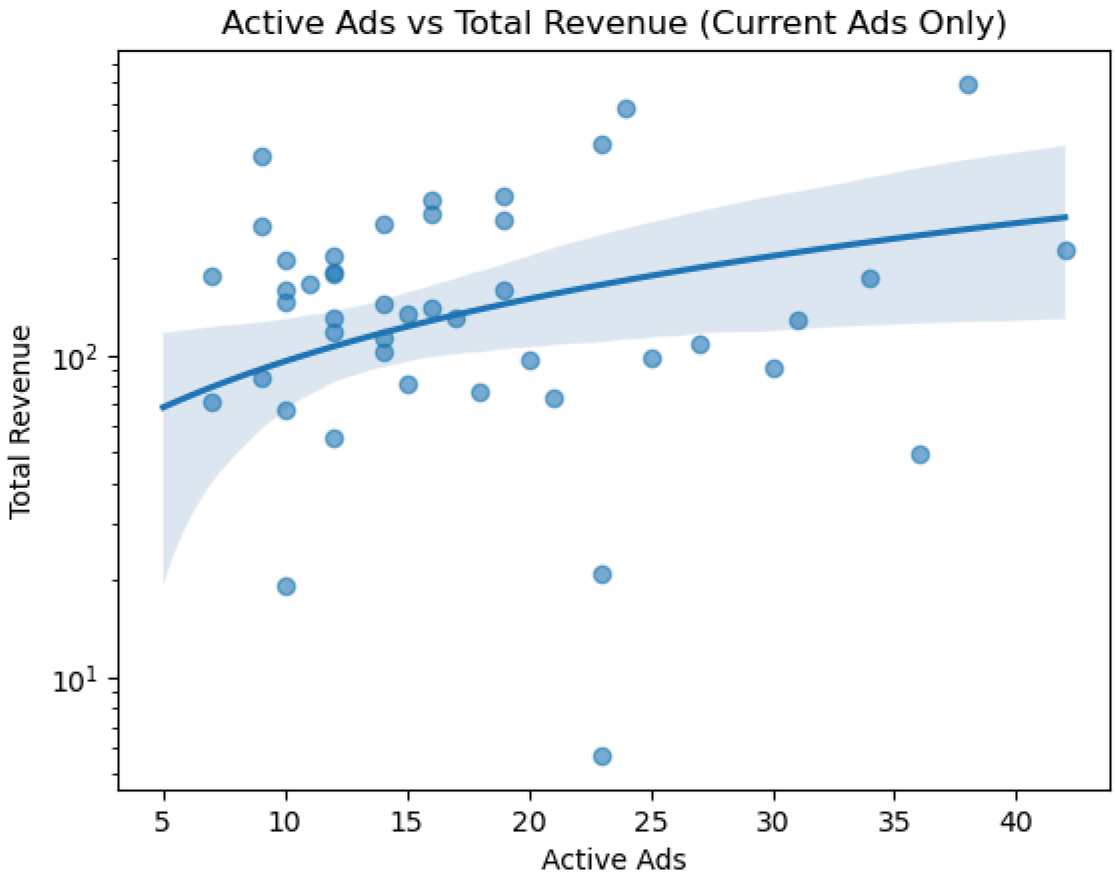
62 rows × 9 columns

In [303…

```
ax = sb.regplot(data=df_5, x="active_ads", y="total_revenue", scatter_kws={'al
ax.set_title("Active Ads vs Total Revenue (Current Ads Only)")
ax.set_xlabel("Active Ads")
ax.set_ylabel("Total Revenue")

ax.set_yscale("log")

plt.show()
```



The regression line trends upward, indicating that on average, advertisers with more active ads also generate more total revenue. However, the wide scatter shows that advertisers with a similar number of ads can achieve very different revenue levels, and several outliers are present.

Conclusion for RQ1: There is evidence of a positive correlation between ad volume and revenue, but correlation does not imply causation. Having more ads does not guarantee higher revenue, though it is often associated with it.

Moving on to Research Question 2: How do ad presentation choices differ across platforms and placements? Specifically, which CTA + format combinations are most commonly used and most effective in driving clicks?

For this analysis, I consider all ads (active and inactive) to capture the full range of presentation strategies.

To begin exploring RQ2, I start with a basic frequency check: counting how many ads use each creative format. This provides a baseline view of how ad presentation formats are distributed across the dataset.

In [323…

```
sql = """
SELECT COUNT(ad_id) "Number of Ads", creative_format "Format"
FROM ad
GROUP BY creative_format
ORDER BY COUNT(ad_id) DESC
```

```
"""
with engine.connect() as conn:
    df_6 = pd.read_sql_query(text(sql), conn)

df_6
```

Out[323]:

	Number of Ads	Format
0	796	video
1	748	image
2	747	text
3	709	carousel

The next step is to examine how creative formats are distributed across different platforms. Adding platform context allows us to see whether certain formats are preferred on specific platforms.

In [325…

```
sql = """
SELECT COUNT(a.ad_id) "Number of Ads", a.creative_format "Format", p.name "Pla
FROM ad a
INNER JOIN Platform p
ON a.platform_id = p.platform_id
GROUP BY p.name, a.creative_format
ORDER BY P.name ASC, COUNT(a.ad_id) DESC
"""
with engine.connect() as conn:
    df_7 = pd.read_sql_query(text(sql), conn)

df_7
```

Out[325]:

	Number of Ads	Format	Platform
0	134	image	Chatter
1	112	video	Chatter
2	109	text	Chatter
3	107	carousel	Chatter
4	143	video	FaceWorld
5	132	image	FaceWorld
6	129	text	FaceWorld
7	104	carousel	FaceWorld
8	137	text	InstaPic
9	131	carousel	InstaPic
10	129	video	InstaPic
11	129	image	InstaPic
12	132	carousel	LinkLine
13	131	video	LinkLine
14	128	text	LinkLine
15	122	image	LinkLine
16	135	video	SnapGram
17	132	text	SnapGram
18	128	carousel	SnapGram
19	103	image	SnapGram
20	146	video	TokTik
21	128	image	TokTik
22	112	text	TokTik
23	107	carousel	TokTik

Next, I calculate what share of each platform's ads belong to each creative format. This highlights how formats are distributed within platforms, not just in overall counts.

In [326…

```
sql = """
WITH total_ads AS (
SELECT a.platform_id, COUNT(a.ad_id) total_ads
FROM ad a
JOIN platform p
ON a.platform_id = p.platform_id
GROUP BY a.platform_id
),

format_ads AS (
SELECT a.platform_id, a.creative_format, COUNT(a.ad_id) format_ads
FROM ad a
GROUP BY a.platform_id, a.creative_format
```

```
)

SELECT
p.name "Platform",
fa.creative_format  "Format",
fa.format_ads AS "Number of Ads",
ROUND(fa.format_ads * 1.0 / t.total_ads, 3) "Share"
FROM format_ads fa
INNER JOIN total_ads t
ON t.platform_id = fa.platform_id
INNER JOIN platform p
ON p.platform_id = fa.platform_id
ORDER BY p.name ASC, "Share" DESC;
"""
with engine.connect() as conn:
    df_8 = pd.read_sql_query(text(sql), conn)

df_8
```

Out[326]:

	Platform	Format	Number of Ads	Share
0	Chatter	video	112	0.242
1	Chatter	image	134	0.290
2	Chatter	text	109	0.236
3	Chatter	carousel	107	0.232
4	FaceWorld	image	132	0.260
5	FaceWorld	text	129	0.254
6	FaceWorld	carousel	104	0.205
7	FaceWorld	video	143	0.282
8	InstaPic	carousel	131	0.249
9	InstaPic	video	129	0.245
10	InstaPic	text	137	0.260
11	InstaPic	image	129	0.245
12	LinkLine	image	122	0.238
13	LinkLine	video	131	0.255
14	LinkLine	carousel	132	0.257
15	LinkLine	text	128	0.250
16	SnapGram	carousel	128	0.257
17	SnapGram	text	132	0.265
18	SnapGram	video	135	0.271
19	SnapGram	image	103	0.207
20	TokTik	image	128	0.260
21	TokTik	video	146	0.296
22	TokTik	text	112	0.227
23	TokTik	carousel	107	0.217

This breakdown enables a more detailed analysis of how each platform allocates its ads across creative formats. It provides context for comparing not only overall volumes but also relative usage patterns by platform.

Next, I examine which CTAs are most frequently used on each platform. This highlights how different platforms emphasize particular calls-to-action.

In [327…

```
sql = """
SELECT COUNT(a.ad_id) "Number of Ads", a.cta "CTA", p.name "Platform"
FROM ad a
INNER JOIN platform p
ON a.platform_id = p.platform_id
GROUP BY p.name, a.cta
ORDER BY p.name ASC, COUNT(a.ad_id) DESC
"""
```

```
with engine.connect() as conn:
    df_9 = pd.read_sql_query(text(sql), conn)

df_9
```

Out[327]:

	Number of Ads	CTA	Platform
0	90	Download	Chatter
1	88	Sign Up	Chatter
2	76	Get Offer	Chatter
3	75	Shop Now	Chatter
4	72	Subscribe	Chatter
5	61	Learn More	Chatter
6	99	Subscribe	FaceWorld
7	90	Shop Now	FaceWorld
8	90	Download	FaceWorld
9	83	Learn More	FaceWorld
10	82	Get Offer	FaceWorld
11	64	Sign Up	FaceWorld
12	99	Subscribe	InstaPic
13	98	Learn More	InstaPic
14	90	Get Offer	InstaPic
15	85	Download	InstaPic
16	77	Shop Now	InstaPic
17	77	Sign Up	InstaPic
18	109	Subscribe	LinkLine
19	88	Sign Up	LinkLine
20	84	Shop Now	LinkLine
21	83	Download	LinkLine
22	82	Get Offer	LinkLine
23	67	Learn More	LinkLine
24	99	Sign Up	SnapGram
25	87	Shop Now	SnapGram
26	82	Download	SnapGram
27	81	Learn More	SnapGram
28	77	Subscribe	SnapGram
29	72	Get Offer	SnapGram
30	88	Get Offer	TokTik
31	87	Shop Now	TokTik
32	83	Subscribe	TokTik
33	80	Download	TokTik
34	79	Sign Up	TokTik

	Number of Ads	CTA	Platform
35	76	Learn More	TokTik

Having gathered frequency data, the analysis now shifts from identifying what is most common to evaluating what is most engaging.

To evaluate engagement, I measure which CTA and creative format combinations generate the most clicks per platform. A LEFT JOIN is used to include all ads while still bringing in performance data when available.

In [328…

```
sql = """
SELECT COUNT(a.ad_id) "Number of Ads", a.cta "CTA", p.name "Platform", SUM(v.c
(SUM(v.clicks) / COUNT(a.ad_id) * 1.0) "avg_clicks_per_ad"
FROM ad a
INNER JOIN platform p
ON a.platform_id = p.platform_id
LEFT JOIN v_ad_performance v
ON a.ad_id = v.ad_id
GROUP BY p.name, a.cta
ORDER BY (SUM(v.clicks) / COUNT(a.ad_id) * 1.0) DESC
"""
with engine.connect() as conn:
    df_10 = pd.read_sql_query(text(sql), conn)

df_10
```

Out[328]:

	Number of Ads	CTA	Platform	Clicks	avg_clicks_per_ad
0	90	Get Offer	InstaPic	94.0	1.0444
1	82	Download	SnapGram	77.0	0.9390
2	87	Shop Now	SnapGram	81.0	0.9310
3	99	Sign Up	SnapGram	92.0	0.9293
4	72	Subscribe	Chatter	64.0	0.8889
5	109	Subscribe	LinkLine	96.0	0.8807
6	81	Learn More	SnapGram	70.0	0.8642
7	87	Shop Now	TokTik	75.0	0.8621
8	88	Sign Up	LinkLine	75.0	0.8523
9	67	Learn More	LinkLine	57.0	0.8507
10	99	Subscribe	InstaPic	84.0	0.8485
11	79	Sign Up	TokTik	66.0	0.8354
12	83	Download	LinkLine	69.0	0.8313
13	99	Subscribe	FaceWorld	82.0	0.8283
14	90	Download	FaceWorld	74.0	0.8222
15	80	Download	TokTik	65.0	0.8125
16	83	Learn More	FaceWorld	67.0	0.8072
17	88	Sign Up	Chatter	71.0	0.8068
18	82	Get Offer	LinkLine	66.0	0.8049
19	98	Learn More	InstaPic	78.0	0.7959
20	72	Get Offer	SnapGram	57.0	0.7917
21	82	Get Offer	FaceWorld	64.0	0.7805
22	77	Shop Now	InstaPic	60.0	0.7792
23	76	Get Offer	Chatter	57.0	0.7500
24	90	Download	Chatter	67.0	0.7444
25	84	Shop Now	LinkLine	62.0	0.7381
26	90	Shop Now	FaceWorld	65.0	0.7222
27	88	Get Offer	TokTik	63.0	0.7159
28	76	Learn More	TokTik	54.0	0.7105
29	83	Subscribe	TokTik	58.0	0.6988
30	61	Learn More	Chatter	42.0	0.6885
31	75	Shop Now	Chatter	50.0	0.6667
32	77	Sign Up	InstaPic	51.0	0.6623
33	85	Download	InstaPic	56.0	0.6588
34	77	Subscribe	SnapGram	50.0	0.6494

	Number of Ads	CTA	Platform	Clicks	avg_clicks_per_ad
35	64	Sign Up	FaceWorld	37.0	0.5781

Next, I connect the pieces by asking: which CTAs are top performers across multiple contexts? This is done by intersecting the most frequently used CTAs with the highest-performing ones. NULLIF is included in the calculation to safely handle cases where no ads are present, avoiding divide-by-zero errors.

In [329…

```
sql = """
WITH cta_counts AS (
SELECT
a.cta cta,
COUNT(a.ad_id) num_ads,
SUM(v.clicks) total_clicks,
SUM(v.clicks) * 1.0 / NULLIF(COUNT(a.ad_id), 0) avg_clicks_per_ad
FROM ad a
LEFT JOIN v_ad_performance v
ON v.ad_id = a.ad_id
GROUP BY a.cta
),

top_freq AS (
SELECT cta
FROM cta_counts
ORDER BY num_ads DESC
LIMIT 5
),

top_engagement AS (
SELECT cta
FROM cta_counts
ORDER BY avg_clicks_per_ad DESC
LIMIT 5
)

SELECT c.cta, c.num_ads, c.total_clicks, c.avg_clicks_per_ad
FROM cta_counts c
INNER JOIN top_freq f
ON f.cta = c.cta
INNER
JOIN top_engagement e
ON e.cta = c.cta
ORDER BY c.avg_clicks_per_ad DESC;
"""
with engine.connect() as conn:
    df_11 = pd.read_sql_query(text(sql), conn)

df_11
```

Out[329]:

	cta	num_ads	total_clicks	avg_clicks_per_ad
0	Get Offer	490	401.0	0.81837
1	Subscribe	539	434.0	0.80519
2	Download	510	408.0	0.80000
3	Sign Up	495	392.0	0.79192

These results represent the CTAs that are both widely used by advertisers and among the strongest performers with users. The intersection approach ensures the list highlights CTAs that succeed on both dimensions: popularity and engagement.

Finally, I compare CTA performance across two specific creative formats: video and image. The goal is to see which CTAs generate the most engagement in video ads compared to image ads.

In [330…

```
sql = """
WITH format_cta AS (
SELECT
a.creative_format,
a.cta,
COUNT(a.ad_id) num_ads,
SUM(v.clicks) total_clicks,
SUM(v.clicks) * 1.0 / NULLIF(COUNT(a.ad_id),0) avg_clicks_per_ad
FROM ad a
LEFT JOIN v_ad_performance v
ON v.ad_id = a.ad_id
WHERE a.creative_format IN ('video','image')
GROUP BY a.creative_format, a.cta
)

SELECT *
FROM format_cta
ORDER BY avg_clicks_per_ad DESC;
"""
with engine.connect() as conn:
    df_12 = pd.read_sql_query(text(sql), conn)

df_12
```

Out[330]:

	creative_format	cta	num_ads	total_clicks	avg_clicks_per_ad
0	image	Learn More	116	109.0	0.93966
1	image	Get Offer	123	106.0	0.86179
2	video	Shop Now	132	111.0	0.84091
3	video	Download	126	105.0	0.83333
4	video	Subscribe	157	130.0	0.82803
5	image	Sign Up	143	117.0	0.81818
6	video	Sign Up	115	93.0	0.80870
7	image	Shop Now	108	87.0	0.80556
8	image	Download	131	105.0	0.80153
9	video	Get Offer	138	105.0	0.76087
10	video	Learn More	128	93.0	0.72656
11	image	Subscribe	127	92.0	0.72441

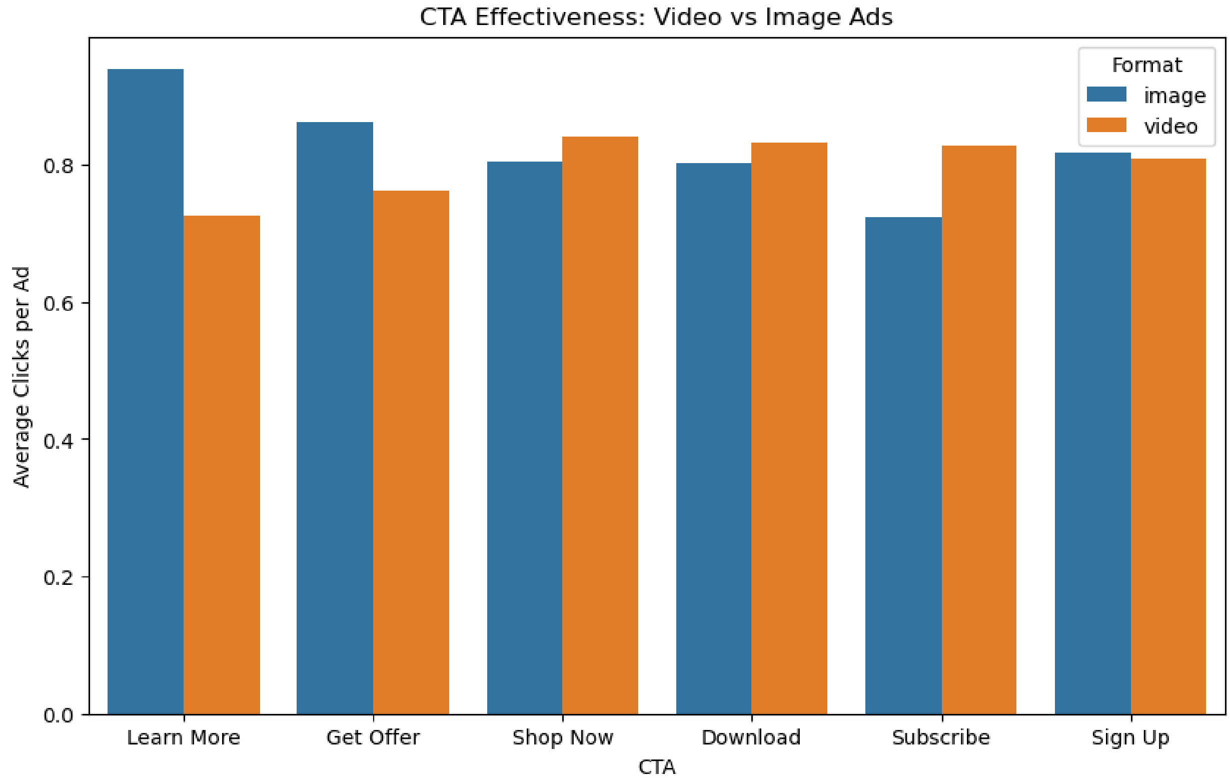
To support the conclusion, I create a visualization. A grouped bar plot is used to compare CTAs by average clicks, with creative format as an additional dimension. This highlights differences in CTA effectiveness between image and video ads.

In [313…

```
plt.figure(figsize=(10,6))
ax = sb.barplot(data=df_12, x="cta", y="avg_clicks_per_ad", hue="creative_forma

ax.set_title("CTA Effectiveness: Video vs Image Ads")
ax.set_xlabel("CTA")
ax.set_ylabel("Average Clicks per Ad")

plt.legend(title="Format")
plt.show()
```



Overall, there is no single format that consistently outperforms the other. Effectiveness depends on the combination of CTA and format: for example, "Learn More" is strongest in image ads, while "Subscribe" performs best in video.

Conclusion for RQ2: Ad presentation choices vary by platform and placement, and performance depends not on the CTA or the format alone, but on how the two are paired together.