YouTube Channel Performance Secrets

Project Objective

This project aims to understand what makes YouTube channels perform well. We will analyze data to find out what helps videos succeed, get more subscribers, and make money. We will use data science techniques to find useful tips and build a predictive model to forecast key metrics such as estimated revenue or subscriber growth based on the analyzed historical data.

Data loading

Load the data from "youtube_channel_real_performance_analytics.csv" into a dataframe.

Import the pandas library and load the CSV file into a DataFrame, then display the first 5 rows.

In [30]:
```
import pandas as pd

df = pd.read_csv('youtube_channel_real_performance_analytics.csv')
display(df.head())
```

	ID	Video Duration	Video Publish Time	Days Since Publish	Day	Month	Year	Day of Week	Revenue per 1000 Views (USD)	Moı Pla (Est
0	0	201.0	2016-06-02 00:00:00	0	2	6	2016	Thursday	0.024	
1	1	391.0	2016-06-10 00:00:00	8	10	6	2016	Friday	0.056	
2	2	133.0	2016-06-14 00:00:00	4	14	6	2016	Tuesday	0.014	
3	3	14.0	2016-06-29 00:00:00	15	29	6	2016	Wednesday	0.004	
4	4	45.0	2016-07-01 00:00:00	2	1	7	2016	Friday	0.000	

5 rows × 70 columns

Data exploration

Explore the data to understand its structure, missing values, and initial distributions of key metrics like views, subscribers, etc. and descriptive statistics of numerical columns.

In [31]:
```python
# Print the shape of the DataFrame
print("Shape of the DataFrame:", df.shape)

# Display the data types of each column
print("\nData types of each column:")
print(df.dtypes)

# Check for missing values in each column
print("\nMissing values per column:")
print(df.isnull().sum())

# Generate information for dataframe
print("\nInformation for the DataFrame:")
print(df.info())

# Generate descriptive statistics for numerical columns
print("\nDescriptive statistics for numerical columns:")
display(df.describe())
```

```
Shape of the DataFrame: (364, 70)

Data types of each column:
ID                           int64
Video Duration             float64
Video Publish Time          object
Days Since Publish           int64
Day                          int64
                            ...
Watch Time (hours)         float64
Subscribers                float64
Estimated Revenue (USD)    float64
Impressions                float64
Video Thumbnail CTR (%)    float64
Length: 70, dtype: object

Missing values per column:
ID                         0
Video Duration             0
Video Publish Time         0
Days Since Publish         0
Day                        0
                          ..
Watch Time (hours)         0
Subscribers                0
Estimated Revenue (USD)    0
Impressions                0
Video Thumbnail CTR (%)    0
Length: 70, dtype: int64

Information for the DataFrame:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 364 entries, 0 to 363
Data columns (total 70 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   ID                                    364 non-null    int64
 1   Video Duration                        364 non-null    float64
 2   Video Publish Time                    364 non-null    object
 3   Days Since Publish                    364 non-null    int64
 4   Day                                   364 non-null    int64
 5   Month                                 364 non-null    int64
 6   Year                                  364 non-null    int64
 7   Day of Week                           364 non-null    object
 8   Revenue per 1000 Views (USD)          364 non-null    float64
 9   Monetized Playbacks (Estimate)        364 non-null    float64
 10  Playback-Based CPM (USD)              364 non-null    float64
 11  CPM (USD)                             364 non-null    float64
 12  Ad Impressions                        364 non-null    float64
 13  Estimated AdSense Revenue (USD)       364 non-null    float64
 14  DoubleClick Revenue (USD)             364 non-null    float64
 15  YouTube Ads Revenue (USD)             364 non-null    float64
 16  Watch Page Ads Revenue (USD)          364 non-null    float64
 17  YouTube Premium (USD)                 364 non-null    float64
```

```
 18  Transaction Revenue (USD)           364 non-null    float64
 19  Transactions                        364 non-null    float64
 20  Revenue from Transactions (USD)     364 non-null    float64
 21  Reactions                           364 non-null    float64
 22  Chat Messages Count                 364 non-null    float64
 23  Reminders Set                       364 non-null    float64
 24  Stream Hours                        364 non-null    float64
 25  Remix Views                         364 non-null    float64
 26  Remix Count                         364 non-null    float64
 27  Subscribers from Posts              364 non-null    float64
 28  New Comments                        364 non-null    float64
 29  Shares                              364 non-null    float64
 30  Like Rate (%)                       364 non-null    float64
 31  Dislikes                            364 non-null    float64
 32  Likes                               364 non-null    float64
 33  Unsubscribes                        364 non-null    float64
 34  New Subscribers                     364 non-null    float64
 35  Returned Items (USD)                364 non-null    float64
 36  Unconfirmed Commissions (USD)       364 non-null    float64
 37  Approved Commissions (USD)          364 non-null    float64
 38  Orders                              364 non-null    float64
 39  Total Sales Volume (USD)            364 non-null    float64
 40  End Screen Click-Through Rate (%)   364 non-null    float64
 41  End Screen Impressions              364 non-null    float64
 42  End Screen Clicks                   364 non-null    float64
 43  Teaser Click-Through Rate (%)       364 non-null    float64
 44  Teaser Impressions                  364 non-null    float64
 45  Teaser Clicks                       364 non-null    float64
 46  Card Click-Through Rate (%)         364 non-null    float64
 47  Card Impressions                    364 non-null    float64
 48  Card Clicks                         364 non-null    float64
 49  Views per Playlist Start            364 non-null    float64
 50  Playlist Views                      364 non-null    float64
 51  Playlist Watch Time (hours)         364 non-null    float64
 52  Clip Watch Time (hours)             364 non-null    float64
 53  Clip Views                          364 non-null    float64
 54  YouTube Premium Watch Time (hours)  364 non-null    float64
 55  YouTube Premium Views               364 non-null    float64
 56  Returning Viewers                   364 non-null    float64
 57  New Viewers                         364 non-null    float64
 58  Average Views per User              364 non-null    float64
 59  Unique Viewers                      364 non-null    float64
 60  Watched (Not Skipped) (%)           364 non-null    float64
 61  Feed Impressions                    364 non-null    float64
 62  Average View Percentage (%)         364 non-null    float64
 63  Average View Duration               364 non-null    float64
 64  Views                               364 non-null    float64
 65  Watch Time (hours)                  364 non-null    float64
 66  Subscribers                         364 non-null    float64
 67  Estimated Revenue (USD)             364 non-null    float64
 68  Impressions                         364 non-null    float64
 69  Video Thumbnail CTR (%)             364 non-null    float64
dtypes: float64(63), int64(5), object(2)
memory usage: 199.2+ KB
```

```
None

Descriptive statistics for numerical columns:
```

	ID	Video Duration	Days Since Publish	Day	Month	Year
count	364.000000	364.000000	364.000000	364.000000	364.000000	364.000000
mean	181.500000	664.239011	8.406593	15.807692	6.642857	2018.736264
std	105.221988	330.646183	15.371239	8.924004	3.421521	2.530629
min	0.000000	9.000000	0.000000	1.000000	1.000000	2016.000000
25%	90.750000	496.000000	3.000000	8.000000	4.000000	2017.000000
50%	181.500000	613.000000	5.000000	16.000000	7.000000	2018.000000
75%	272.250000	786.500000	9.000000	23.000000	10.000000	2021.000000
max	363.000000	2311.000000	260.000000	31.000000	12.000000	2024.000000

8 rows × 68 columns

Identify the categorical columns and get the unique values and their counts for these columns.

In [32]:

```python
# Get the unique values and their counts for categorical columns (object dtype
categorical_cols = df.select_dtypes(include='object').columns

print("\nUnique values and counts for categorical columns:")
for col in categorical_cols:
    print(f"\nColumn: {col}")
    print(df[col].value_counts())
```

```
Unique values and counts for categorical columns:

Column: Video Publish Time
Video Publish Time
2017-06-09 00:00:00    2
2017-03-24 00:00:00    2
2017-02-23 00:00:00    2
2017-04-30 00:00:00    2
2017-07-05 00:00:00    2
                      ..
2017-08-07 00:00:00    1
2017-08-05 00:00:00    1
2017-08-04 00:00:00    1
2017-08-02 00:00:00    1
2017-08-21 00:00:00    1
Name: count, Length: 357, dtype: int64

Column: Day of Week
Day of Week
Sunday       63
Tuesday      60
Wednesday    57
Friday       54
Saturday     49
Monday       46
Thursday     35
Name: count, dtype: int64
```

Data cleaning

Clean the data by handling missing values, removing duplicates, and addressing any inconsistencies or errors identified during the data exploration phase. The data exploration showed that 'Video Publish Time' is of object type and needs conversion to datetime. Missing values and duplicate rows will be removed.

In [33]:

```python
# Handle missing values and drop rows with any missing values
df.dropna(inplace=True)
print("Shape after dropping rows with missing values:", df.shape)

# Remove duplicate rows
df.drop_duplicates(inplace=True)
print("Shape after dropping duplicate rows:", df.shape)

# Handle data type inconsistencies
# Convert 'Video Publish Time' to datetime objects
df['Video Publish Time'] = pd.to_datetime(df['Video Publish Time'])
print("\nData types after converting 'Video Publish Time':")
print(df['Video Publish Time'].dtypes)

display(df.head())
```

```
Shape after dropping rows with missing values: (364, 70)
Shape after dropping duplicate rows: (364, 70)

Data types after converting 'Video Publish Time':
datetime64[ns]
```

	ID	Video Duration	Video Publish Time	Days Since Publish	Day	Month	Year	Day of Week	Revenue per 1000 Views (USD)	Mo Pla (Es
0	0	201.0	2016-06-02	0	2	6	2016	Thursday	0.024	
1	1	391.0	2016-06-10	8	10	6	2016	Friday	0.056	
2	2	133.0	2016-06-14	4	14	6	2016	Tuesday	0.014	
3	3	14.0	2016-06-29	15	29	6	2016	Wednesday	0.004	
4	4	45.0	2016-07-01	2	1	7	2016	Friday	0.000	

5 rows × 70 columns

Data wrangling

Perform data wrangling to prepare the cleaned data for analysis. This includes extracting relevant information from existing columns and creating new features if necessary. Extract year, month, day, hour, and day of the week from 'Video Publish Time' and convert 'Video Duration' to seconds.

In [34]:

```
# Extract year, month, and day from 'Video Publish Time'
df['Publish Year'] = df['Video Publish Time'].dt.year
df['Publish Month'] = df['Video Publish Time'].dt.month
df['Publish Day'] = df['Video Publish Time'].dt.day

# Extract the hour from 'Video Publish Time'
df['Publish Hour'] = df['Video Publish Time'].dt.hour

# Create a new feature for the day of the week
df['Publish Day of Week'] = df['Video Publish Time'].dt.day_name()

# Display the new columns and the original 'Video Duration'
display(df[['Video Publish Time', 'Publish Year', 'Publish Month', 'Publish Da
```

	Video Publish Time	Publish Year	Publish Month	Publish Day	Publish Hour	Publish Day of Week	Video Duration
0	2016-06-02	2016	6	2	0	Thursday	201.0
1	2016-06-10	2016	6	10	0	Friday	391.0
2	2016-06-14	2016	6	14	0	Tuesday	133.0
3	2016-06-29	2016	6	29	0	Wednesday	14.0
4	2016-07-01	2016	7	1	0	Friday	45.0

Data analysis

Analyze the wrangled data to identify patterns and correlations between different performance metrics and channel characteristics.

In [35]:
```
# Select relevant numerical columns for correlation analysis
performance_metrics = ['Views', 'Watch Time (hours)', 'Subscribers', 'Estimate

# Calculate the correlation matrix
correlation_matrix = df[performance_metrics].corr()

# Display the correlation matrix
display(correlation_matrix)
```

	Views	Watch Time (hours)	Subscribers	Estimated Revenue (USD)	Video Duration	Impressions
Views	1.000000	0.931054	0.802406	0.357901	-0.051500	0.870877
Watch Time (hours)	0.931054	1.000000	0.728458	0.431998	0.111037	0.871523
Subscribers	0.802406	0.728458	1.000000	0.418177	-0.025584	0.818828
Estimated Revenue (USD)	0.357901	0.431998	0.418177	1.000000	0.135767	0.469940
Video Duration	-0.051500	0.111037	-0.025584	0.135767	1.000000	0.039546
Impressions	0.870877	0.871523	0.818828	0.469940	0.039546	1.000000
Video Thumbnail CTR (%)	0.377969	0.318551	0.167714	0.059658	-0.190195	0.155179
Average View Percentage (%)	-0.134378	-0.103977	-0.103119	-0.022337	-0.480500	-0.072227
Average View Duration	-0.046536	0.153607	-0.032361	0.207286	0.881891	0.055428

Analyze average performance metrics grouped by temporal features to identify trends related to publishing time.

In [36]:
```
# Group by 'Publish Year' and calculate the mean of performance metrics
avg_performance_by_year = df.groupby('Publish Year')[performance_metrics].mear
print("Average Performance by Publish Year:")
display(avg_performance_by_year)

# Group by 'Publish Month' and calculate the mean of performance metrics
avg_performance_by_month = df.groupby('Publish Month')[performance_metrics].me
print("\nAverage Performance by Publish Month:")
display(avg_performance_by_month)

# Group by 'Publish Day of Week' and calculate the mean of performance metrics
# Ensure days are in order for potential plotting later (Monday to Sunday)
days_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturda
avg_performance_by_day_of_week = df.groupby('Publish Day of Week')[performance
print("\nAverage Performance by Publish Day of Week:")
display(avg_performance_by_day_of_week)

# Group by 'Publish Hour' and calculate the mean of performance metrics
avg_performance_by_hour = df.groupby('Publish Hour')[performance_metrics].mear
```

```
print("\nAverage Performance by Publish Hour:")
display(avg_performance_by_hour)
```

```
Average Performance by Publish Year:
```

Publish Year	Views	Watch Time (hours)	Subscribers	Estimated Revenue (USD)	Video Duration	Impre
2016	33046.525000	1915.988613	108.500000	1.992925	540.450000	1.21210
2017	134087.000000	9587.876524	257.441176	7.368419	644.235294	6.87152
2018	247245.266667	18869.799042	652.083333	6.031800	588.633333	2.19781
2019	221441.166667	17029.790322	588.944444	12.674944	586.166667	1.80793
2020	165340.933333	16349.723733	415.066667	18.045800	743.600000	1.34813
2021	80896.038462	7621.944608	366.038462	20.736423	673.115385	8.87952
2022	104067.304348	9988.625361	307.782609	15.367130	675.608696	1.09487
2023	72119.700000	7742.168510	291.600000	14.474000	805.900000	1.03637
2024	22409.194444	2543.667264	56.583333	6.729167	956.305556	2.13917

```
Average Performance by Publish Month:
```

Publish Month	Views	Watch Time (hours)	Subscribers	Estimated Revenue (USD)	Video Duration	Impre
1	100782.500000	8348.136550	232.566667	6.030500	755.700000	8.37739
2	105323.500000	8089.346763	202.083333	7.673833	752.416667	8.61016
3	106192.468750	8557.916225	355.156250	6.289000	707.812500	8.78479
4	124569.928571	10850.776107	337.392857	8.660571	696.392857	1.10605
5	91280.240000	7456.405488	204.440000	5.973440	616.640000	7.10637
6	118248.750000	8544.602594	244.111111	7.140972	573.388889	7.81690
7	161448.406250	11650.170550	340.218750	9.229437	613.781250	8.73934
8	125892.764706	9504.593418	262.823529	11.303029	592.911765	7.51642
9	153248.333333	10985.135280	344.666667	6.607467	611.933333	1.12003
10	181558.750000	15395.113586	499.178571	18.373571	697.750000	1.58378
11	142134.171429	11198.277074	407.685714	12.236371	731.257143	1.08649
12	126814.200000	9888.851867	396.866667	6.210100	651.933333	9.66267

Average Performance by Publish Day of Week:

Publish Day of Week	Views	Watch Time (hours)	Subscribers	Estimated Revenue (USD)	Video Duration	In
Monday	132124.043478	10468.418752	277.282609	10.012587	643.760870	9.2
Tuesday	116269.566667	8862.573340	319.716667	10.987400	681.950000	1.0
Wednesday	130479.912281	9791.847530	264.701754	6.012842	620.754386	9.0
Thursday	110206.800000	9516.884269	245.114286	11.287686	782.771429	9.2
Friday	142267.037037	11058.118544	467.870370	9.955352	612.388889	1.0
Saturday	122990.693878	9560.652047	299.571429	7.834959	662.714286	8.0
Sunday	140092.063492	10973.415119	338.158730	7.032079	681.444444	1.0

Average Performance by Publish Hour:

	Views	Watch Time (hours)	Subscribers	Estimated Revenue (USD)	Video Duration	Impr
Publish Hour						
0	128800.101648	10058.965455	321.024725	8.852052	664.239011	959528

Analyze average performance metrics grouped by categorical features other than temporal ones. Since no explicit categorical features were identified beyond temporal ones in the exploration phase, this step might not yield significant results unless implicit categorical data exists or needs creation. I will check for object type columns again and group by them if they seem relevant to performance.

In [37]:

```python
# Identify potential categorical columns again (excluding temporal ones alreac
# Let's re-check object type columns and exclude the 'Video Publish Time' and
categorical_cols_check = df.select_dtypes(include='object').columns.tolist()
temporal_categorical_cols = ['Video Publish Time', 'Publish Day of Week'] # Vi
relevant_categorical_cols = [col for col in categorical_cols_check if col not

print("Potential relevant categorical columns for grouping:", relevant_categor

# If there are relevant categorical columns, group by them and calculate mean
if relevant_categorical_cols:
    for col in relevant_categorical_cols:
        print(f"\nAnalyzing average performance by '{col}':")
        try:
            avg_performance_by_category = df.groupby(col)[performance_metrics]
            display(avg_performance_by_category)
        except Exception as e:
            print(f"Could not group by {col}: {e}")
else:
    print("\nNo additional relevant categorical columns found for grouping ana
```

```
Potential relevant categorical columns for grouping: ['Day of Week']

Analyzing average performance by 'Day of Week':
```

Day of Week	Views	Watch Time (hours)	Subscribers	Estimated Revenue (USD)	Video Duration	In
Friday	142267.037037	11058.118544	467.870370	9.955352	612.388889	1.0
Monday	132124.043478	10468.418752	277.282609	10.012587	643.760870	9.2
Saturday	122990.693878	9560.652047	299.571429	7.834959	662.714286	8.0
Sunday	140092.063492	10973.415119	338.158730	7.032079	681.444444	1.0
Thursday	110206.800000	9516.884269	245.114286	11.287686	782.771429	9.2
Tuesday	116269.566667	8862.573340	319.716667	10.987400	681.950000	1.0
Wednesday	130479.912281	9791.847530	264.701754	6.012842	620.754386	9.0

Key findings from the correlation analysis

1. Correlation Analysis:

- Strong positive correlations observed between Views, Watch Time (hours), Subscribers, and Impressions. This suggests that as a video gains views, it generally also gets more watch time, subscribers, and impressions, indicating a healthy growth loop.

- Estimated Revenue (USD) shows moderate positive correlations with Views, Watch Time, and Subscribers. Higher engagement and audience size generally translate to higher estimated revenue.

- Video Duration has a strong positive correlation with Average View Duration, as expected. It also shows a moderate negative correlation with Average View Percentage, meaning longer videos tend to have a lower percentage of the video watched, even if the absolute duration watched is higher.

- Video Thumbnail CTR (%) shows a moderate positive correlation with Views, highlighting the importance of compelling thumbnails for initial clicks.

2. Temporal Analysis:

- Publish Year: Performance metrics generally increased over the years, potentially reflecting channel growth or changes in content strategy, but show a dip in the most recent partial year (2024).

- Publish Month: There appear to be variations in average performance across months, with potentially higher performance in certain months (e.g., October, November) for some metrics.
- Publish Day of Week: Performance metrics show some variation across days of the week. Friday and Sunday appear to have higher average views and watch time compared to other days.
- Publish Hour: The grouping by hour currently shows only one hour (0). This suggests the 'Publish Hour' feature might not be granular enough or the data might be concentrated at midnight UTC. Further investigation or different time zone handling might be needed here.

3. Categorical Analysis (by Day of Week):

The analysis by 'Day of Week' (which is the same as 'Publish Day of Week' already analyzed) confirms the trend that Fridays and Sundays tend to perform better on average in terms of Views and Watch Time.

YouTube Channel Performance Secrets

Based on this preliminary analysis, here are some potential 'secrets':

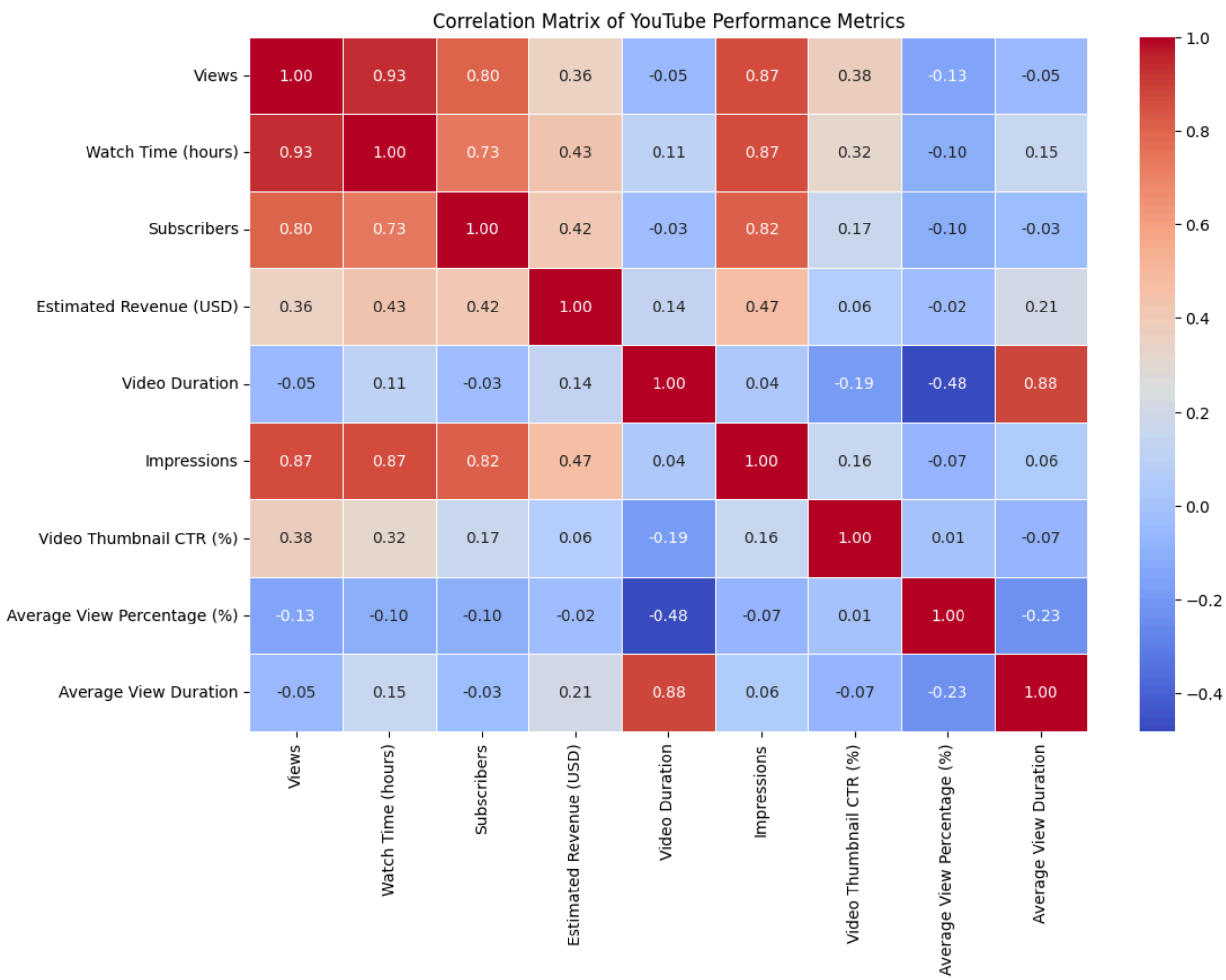
1. The core metrics (Views, Watch Time, Subscribers, Impressions) are highly interconnected; focusing on improving one can positively impact the others.
2. Compelling video thumbnails (high CTR) are important for driving initial views.
3. While longer videos can result in higher average watch duration, maintaining a high average view percentage across different video lengths is crucial.
4. Publishing on certain days of the week, particularly Fridays and Sundays, might lead to higher initial engagement.
5. There might be seasonal trends in performance (indicated by monthly variations).

Data visualization

Create visualizations to illustrate key findings from the analysis, such as trends in views over time, subscriber growth by content type, correlation heatmaps, and performance by time of day/week.

Generate a heatmap for the correlation matrix to visualize the relationships between performance metrics.

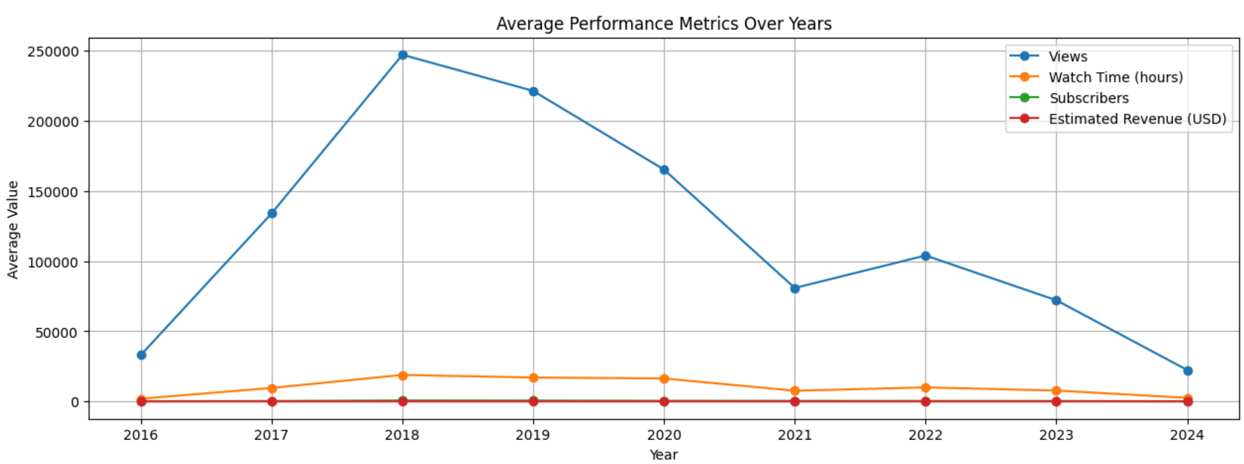
In [38]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewi
plt.title('Correlation Matrix of YouTube Performance Metrics')
plt.show()
```

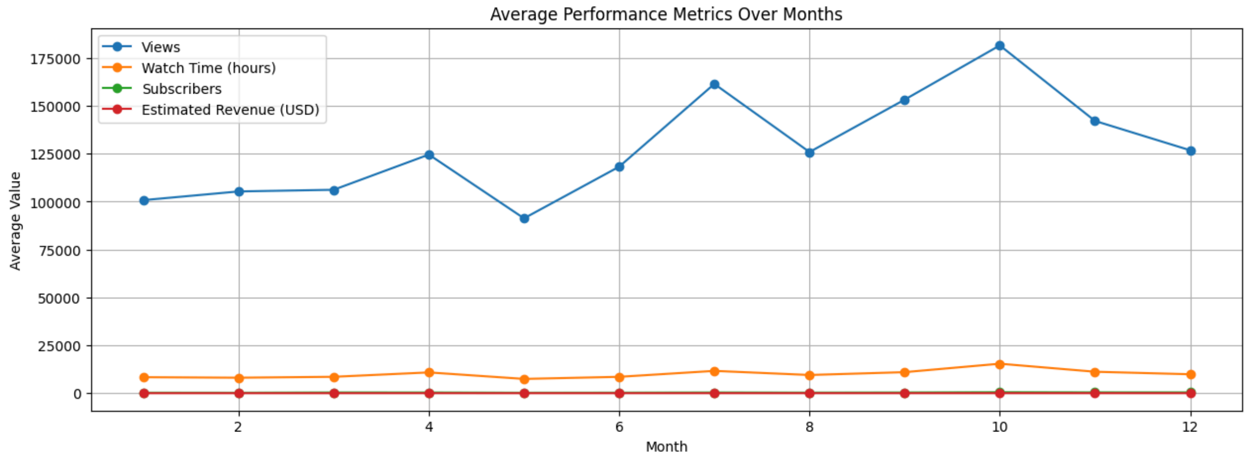


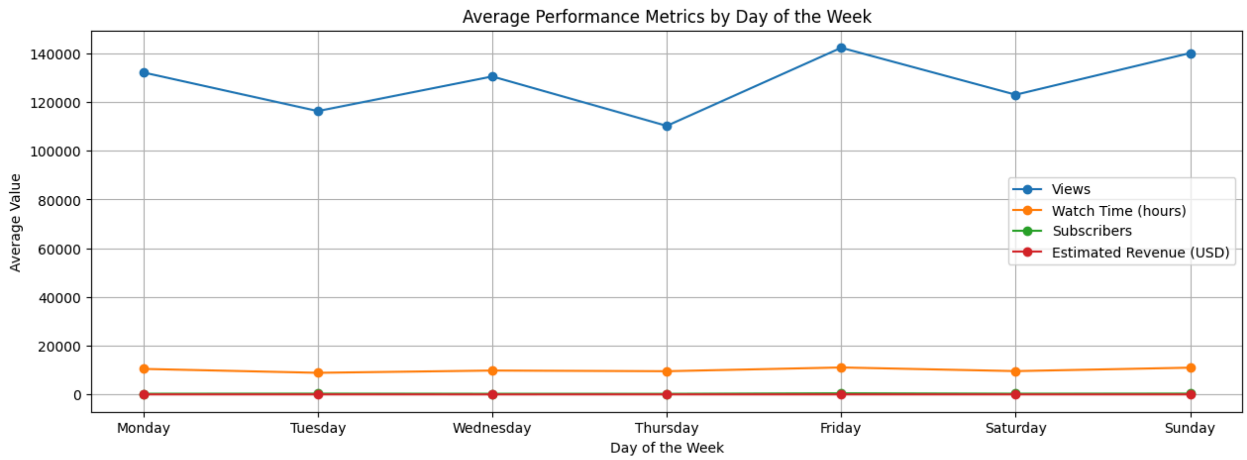
Generate line plots to visualize the trends in average performance metrics over time by year, month, and day of the week using the previously created grouped dataframes.

In [39]:
```
# Define the list of performance metrics to plot
performance_metrics_to_plot = ['Views', 'Watch Time (hours)', 'Subscribers', '

# Plot trends over the years
plt.figure(figsize=(15, 5))
```

```python
for metric in performance_metrics_to_plot:
    plt.plot(avg_performance_by_year.index, avg_performance_by_year[metric], m
plt.title('Average Performance Metrics Over Years')
plt.xlabel('Year')
plt.ylabel('Average Value')
plt.legend()
plt.grid(True)
plt.show()

# Plot trends over the months
plt.figure(figsize=(15, 5))
for metric in performance_metrics_to_plot:
    plt.plot(avg_performance_by_month.index, avg_performance_by_month[metric],
plt.title('Average Performance Metrics Over Months')
plt.xlabel('Month')
plt.ylabel('Average Value')
plt.legend()
plt.grid(True)
plt.show()

# Plot trends over the days of the week
plt.figure(figsize=(15, 5))
for metric in performance_metrics_to_plot:
    plt.plot(avg_performance_by_day_of_week.index, avg_performance_by_day_of_w
plt.title('Average Performance Metrics by Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Average Value')
plt.legend()
plt.grid(True)
plt.show()
```



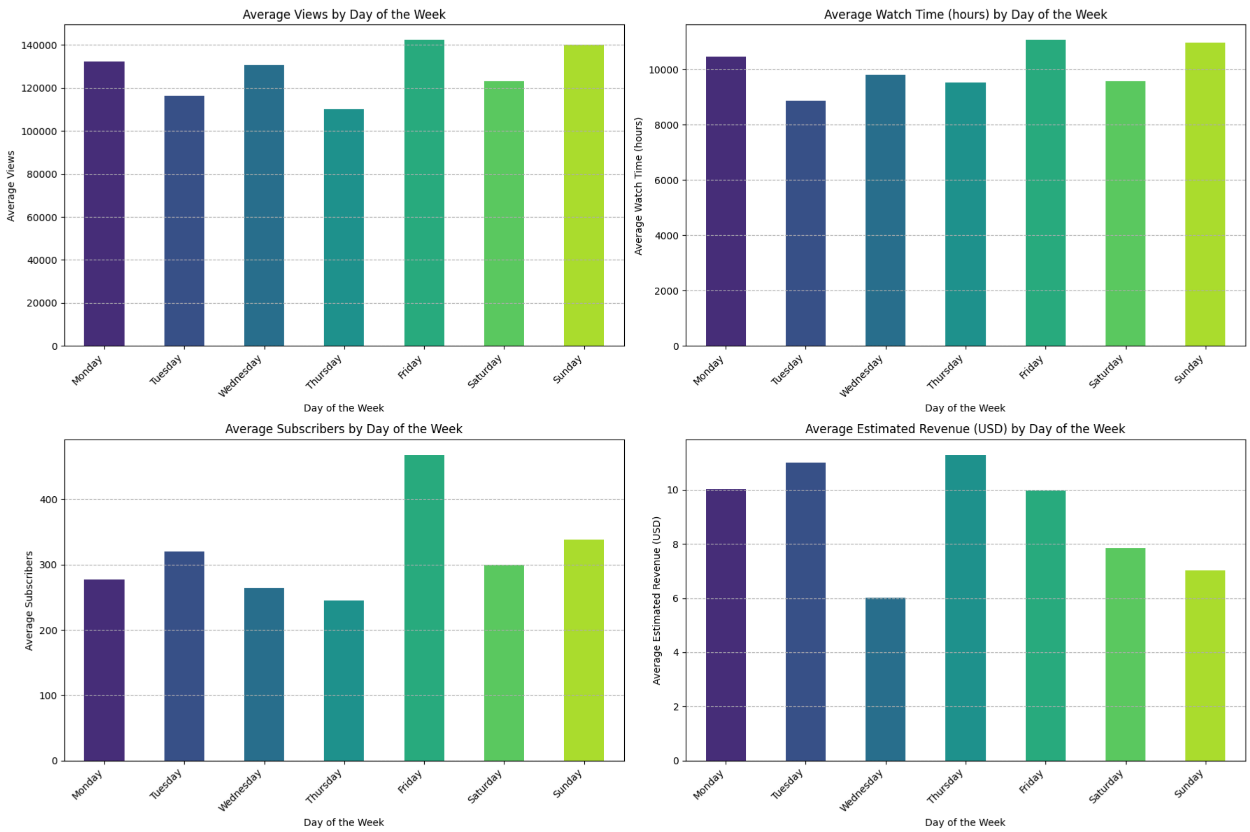




The previous step plotted trends over time. Since 'Day of Week' was identified as a relevant categorical column in the analysis phase and its average performance was calculated, generate bar plots to visualize the average performance metrics for each day of the week, as instructed in step 3.

In [40]:

```
# Plot bar plots for average performance by Day of Week for key metrics
metrics_for_bar_plot = ['Views', 'Watch Time (hours)', 'Subscribers', 'Estimat
days_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturda

plt.figure(figsize=(18, 12))

for i, metric in enumerate(metrics_for_bar_plot):
    plt.subplot(2, 2, i + 1) # Create a 2x2 grid of subplots
    avg_performance_by_day_of_week[metric].plot(kind='bar', color=sns.color_pa
    plt.title(f'Average {metric} by Day of the Week')
    plt.xlabel('Day of the Week')
    plt.ylabel(f'Average {metric}')
    plt.xticks(rotation=45, ha='right') # Rotate labels for better readability
    plt.grid(axis='y', linestyle='--')

plt.tight_layout() # Adjust layout to prevent overlapping
plt.show()
```



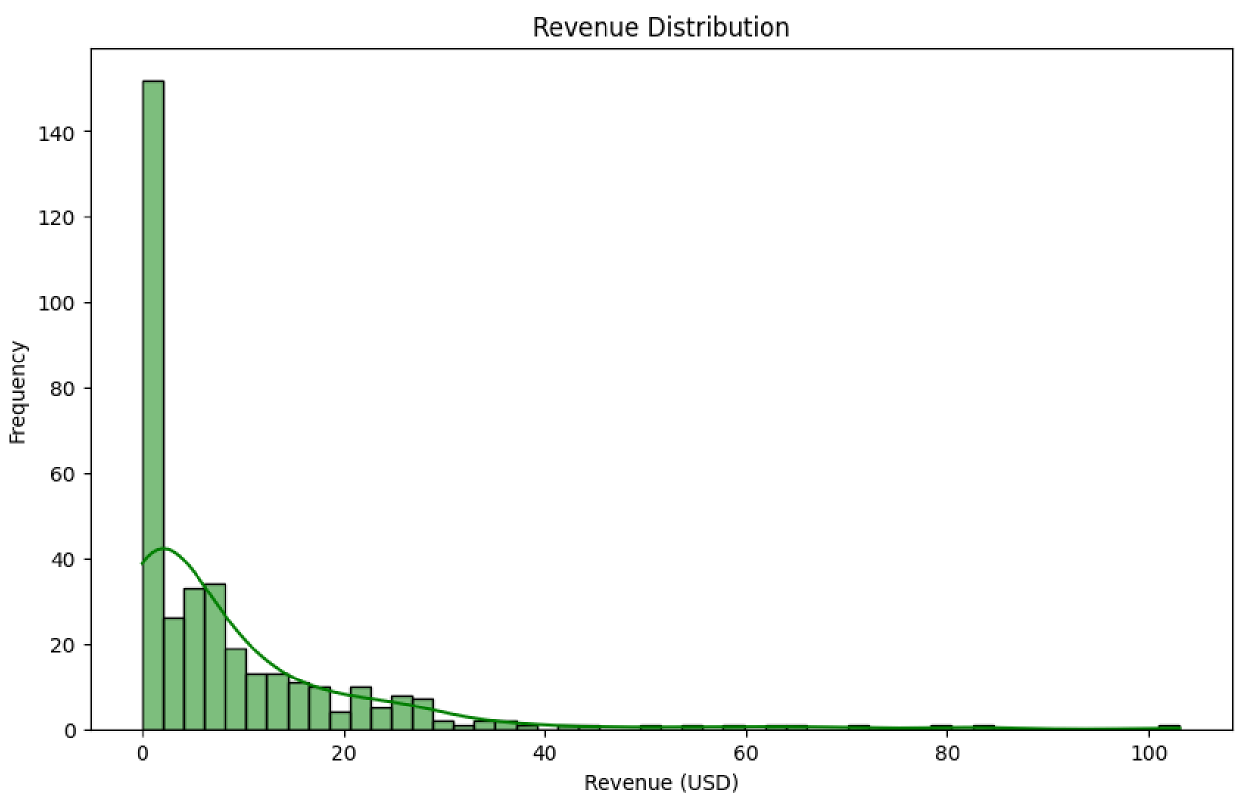
In [41]:

```
# Top Performers by Revenue

# Sort the DataFrame by 'Estimated Revenue (USD)' in descending order and sele
top_revenue_videos = df.sort_values(by='Estimated Revenue (USD)', ascending=Fa

# Display the top 10 videos by estimated revenue (you can adjust the number as
print("Top 10 Videos by Estimated Revenue (USD):")
display(top_revenue_videos[['ID', 'Estimated Revenue (USD)', 'Views', 'Subscri
```

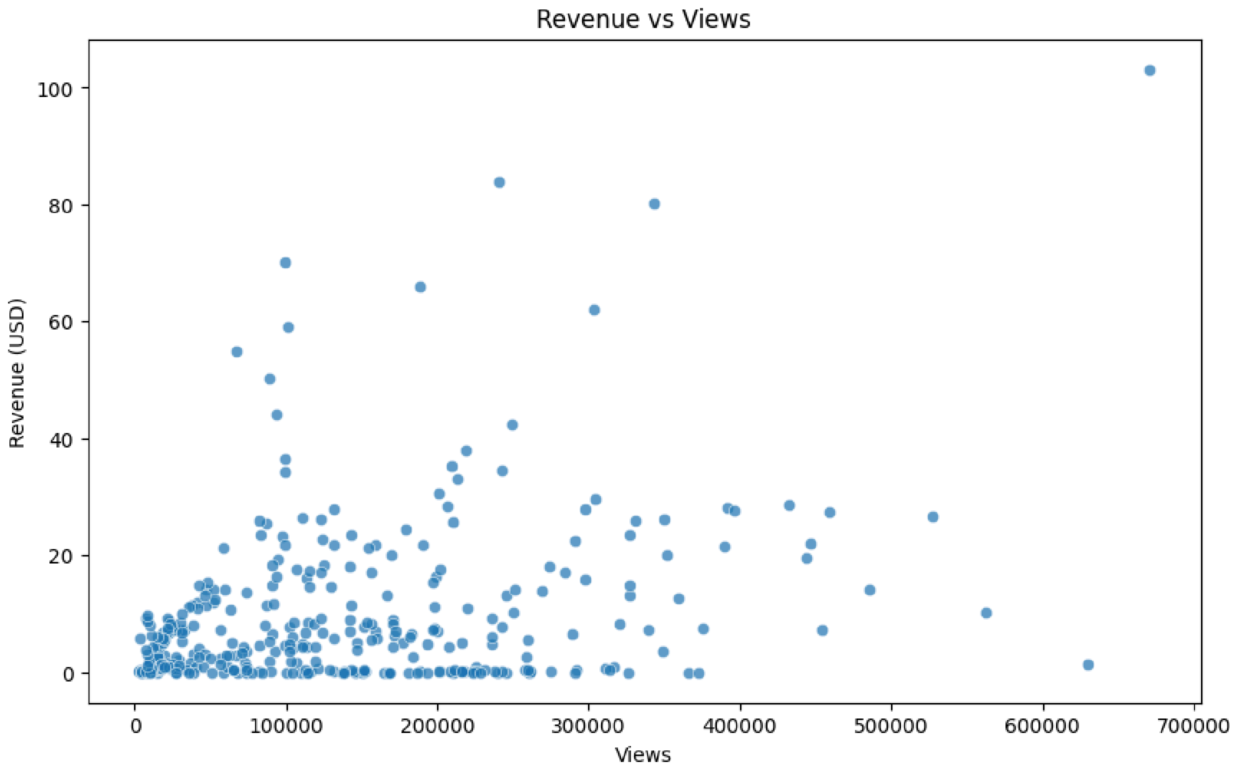
```
Top 10 Videos by Estimated Revenue (USD):
```

	ID	Estimated Revenue (USD)	Views	Subscribers
228	228	103.117	670990.0	3538.0
257	257	83.979	241060.0	1125.0
251	251	80.265	343319.0	1437.0
289	289	70.247	99196.0	350.0
278	278	65.978	188324.0	1824.0
260	260	62.047	302999.0	866.0
293	293	59.058	101025.0	602.0
294	294	55.040	67556.0	581.0
290	290	50.344	89284.0	995.0
284	284	44.228	93487.0	305.0

In [42]:
```
#Revenue Distribution
plt.figure(figsize=(10, 6))
sns.histplot(df['Estimated Revenue (USD)'], bins=50,
kde=True, color='green')
plt.title("Revenue Distribution")
plt.xlabel("Revenue (USD)")
plt.ylabel("Frequency")
plt.show()
```



In [43]:
```
# Revenue vs Views
plt.figure(figsize=(10, 6))
sns.scatterplot(x=df['Views'], y=df['Estimated Revenue (USD)'], alpha=0.7)
plt.title("Revenue vs Views")
plt.xlabel("Views")
plt.ylabel("Revenue (USD)")
plt.show()
```



In [44]:
```
# Feature Engineering
# Create new features:

# Create revenue per view
df['Revenue per View'] = df['Estimated Revenue (USD)'] / df['Views']

# Create engagement rate
df['Engagement Rate'] = (df['Likes'] + df['Shares'] + df['New Comments']) / df
```

Predictive modeling

In [45]:
```
# Develop a predictive model to estimate revenue or subscribers based on the p

# Develop a linear regression model to predict 'Estimated Revenue (USD)' using
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score, root_mean_squared_er
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
```

```python
import numpy as np
```

In [46]:
```python
# Define features (X) and target (y)
# Selecting relevant numerical features that showed correlation with revenue
features = ['Views', 'Watch Time (hours)', 'Subscribers', 'Video Duration', 'I
target = 'Estimated Revenue (USD)'

X = df[features]
y = df[target]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
```

In [47]:
```python
# Initialize and train the Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)
```

In [48]:
```python
# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
rmse = root_mean_squared_error(y_test, y_pred) # Calculate RMSE
r2 = r2_score(y_test, y_pred)

print("\nLinear Regression Model Evaluation:")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"R-squared (R2): {r2:.2f}")

# Optionally, print the model coefficients
print("\nModel Coefficients:")
for feature, coef in zip(features, model.coef_):
    print(f"{feature}: {coef:.2f}")

print(f"\nIntercept: {model.intercept_:.2f}") # Changed model.intercept to moc
```

```
Linear Regression Model Evaluation:
Mean Squared Error (MSE): 106.73
Root Mean Squared Error (RMSE): 10.33
R-squared (R2): -0.23

Model Coefficients:
Views: -0.00
Watch Time (hours): 0.00
Subscribers: 0.01
Video Duration: -0.01
Impressions: 0.00
Video Thumbnail CTR (%): -0.05
Average View Percentage (%): -0.13
Average View Duration: 0.00
Revenue per View: 50288.99
Engagement Rate: -0.56

Intercept: 15.86
```

In [49]:

```
# Initialize and train the Random Forest Regressor model
# You can tune hyperparameters like n_estimators (number of trees)
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_rf = rf_model.predict(X_test)
```

In [50]:

```
# Evaluate the model
mse_rf = mean_squared_error(y_test, y_pred_rf)
rmse_rf = np.sqrt(mse_rf) # RMSE is the square root of MSE
r2_rf = r2_score(y_test, y_pred_rf)

print("\nRandom Forest Regressor Model Evaluation:")
print(f"Mean Squared Error (MSE): {mse_rf:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse_rf:.2f}")
print(f"R-squared (R2): {r2_rf:.2f}")

# You can also get feature importances from tree-based models
print("\nFeature Importances (Random Forest):")
feature_importances = pd.Series(rf_model.feature_importances_, index=features)
print(feature_importances)
```

```
Random Forest Regressor Model Evaluation:
Mean Squared Error (MSE): 6.49
Root Mean Squared Error (RMSE): 2.55
R-squared (R2): 0.93

Feature Importances (Random Forest):
Revenue per View                0.394507
Subscribers                     0.235948
Impressions                     0.138946
Watch Time (hours)              0.096377
Views                           0.084076
Engagement Rate                 0.013641
Video Thumbnail CTR (%)         0.011911
Average View Duration           0.010354
Average View Percentage (%)     0.007971
Video Duration                  0.006271
dtype: float64
```

In [51]:

```python
# Initialize and train the Gradient Boosting Regressor model
# You can tune hyperparameters like n_estimators, learning_rate, max_depth, et
gbr_model = GradientBoostingRegressor(n_estimators=100, learning_rate=0.1, max
gbr_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_gbr = gbr_model.predict(X_test)
```

In [52]:

```python
# Evaluate the model
mse_gbr = mean_squared_error(y_test, y_pred_gbr)
rmse_gbr = np.sqrt(mse_gbr)
r2_gbr = r2_score(y_test, y_pred_gbr)

print("\nGradient Boosting Regressor Model Evaluation:")
print(f"Mean Squared Error (MSE): {mse_gbr:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse_gbr:.2f}")
print(f"R-squared (R2): {r2_gbr:.2f}")

# Get feature importances
print("\nFeature Importances (Gradient Boosting):")
feature_importances_gbr = pd.Series(gbr_model.feature_importances_, index=feat
print(feature_importances_gbr)
```

```
Gradient Boosting Regressor Model Evaluation:
Mean Squared Error (MSE): 3.03
Root Mean Squared Error (RMSE): 1.74
R-squared (R2): 0.97

Feature Importances (Gradient Boosting):
Revenue per View                0.366819
Subscribers                     0.329784
Impressions                     0.121353
Views                           0.099915
Watch Time (hours)              0.055956
Video Thumbnail CTR (%)         0.013287
Average View Percentage (%)     0.011167
Engagement Rate                 0.000909
Average View Duration           0.000596
Video Duration                  0.000214
dtype: float64
```

In [53]:

```python
# Import the Support Vector Regressor
from sklearn.svm import SVR
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
```

In [54]:

```python
# Initialize and train the Support Vector Regressor model
# SVR is sensitive to feature scaling, so it's good practice to scale the feat
# We can use a pipeline to combine scaling and the SVR model.
svr_model = make_pipeline(StandardScaler(), SVR(C=1.0, epsilon=0.2)) # You can

# Fit the model on the training data
# The pipeline handles the scaling internally
svr_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_svr = svr_model.predict(X_test)
```

In [55]:

```python
# Evaluate the model
mse_svr = mean_squared_error(y_test, y_pred_svr)
rmse_svr = np.sqrt(mse_svr)
r2_svr = r2_score(y_test, y_pred_svr)

print("\nSupport Vector Regressor Model Evaluation:")
print(f"Mean Squared Error (MSE): {mse_svr:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse_svr:.2f}")
print(f"R-squared (R2): {r2_svr:.2f}")
```

```
Support Vector Regressor Model Evaluation:
Mean Squared Error (MSE): 54.52
Root Mean Squared Error (RMSE): 7.38
R-squared (R2): 0.37
```

In [56]:

```python
# Import the K-Nearest Neighbors Regressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.preprocessing import StandardScaler
```

```python
from sklearn.pipeline import make_pipeline
```

In [57]:
```python
# Initialize and train the K-Nearest Neighbors Regressor model
# KNN is sensitive to feature scaling, so it's good practice to scale the feat
# We can use a pipeline to combine scaling and the KNN model.
knn_model = make_pipeline(StandardScaler(), KNeighborsRegressor(n_neighbors=5)

# Fit the model on the training data
# The pipeline handles the scaling internally
knn_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_knn = knn_model.predict(X_test)
```

In [58]:
```python
# Evaluate the model
mse_knn = mean_squared_error(y_test, y_pred_knn)
rmse_knn = np.sqrt(mse_knn)
r2_knn = r2_score(y_test, y_pred_knn)

print("\nK-Nearest Neighbors Regressor Model Evaluation:")
print(f"Mean Squared Error (MSE): {mse_knn:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse_knn:.2f}")
print(f"R-squared (R2): {r2_knn:.2f}")

# Note: KNN models do not have a concept of feature importance in the same way
```

```
K-Nearest Neighbors Regressor Model Evaluation:
Mean Squared Error (MSE): 62.69
Root Mean Squared Error (RMSE): 7.92
R-squared (R2): 0.28
```

Summary:

Data Analysis Key Findings

- Core metrics like Views, Watch Time, Subscribers, and Impressions are strongly positively correlated.
- Estimated Revenue has moderate positive correlations with Views, Watch Time, and Subscribers.
- Video Thumbnail CTR (%) shows a moderate positive correlation with Views, indicating its importance for initial engagement.
- Video Duration is strongly positively correlated with Average View Duration but moderately negatively correlated with Average View Percentage.
- Performance metrics generally increased over the years but show a dip in the most recent partial year (2024).
- Monthly variations in performance are observed, with potentially higher averages in October and November for some metrics.

- Fridays and Sundays tend to have higher average Views and Watch Time compared to other days of the week.
- Analysis of average performance by Publish Hour was inconclusive based on the provided data.

Based on the evaluation metrics, the **Gradient Boosting Regressor** is the best performing model among those tested. It exhibits the lowest **Mean Squared Error (MSE)** (3.03) and **Root Mean Squared Error (RMSE)** (1.74), indicating the smallest average prediction errors. Furthermore, its **R-squared (R2)** value of 0.97 is the highest, meaning it explains 97% of the variance in the target variable (Estimated Revenue), which signifies a strong fit to the data. The **Random Forest Regressor** is also a good performer with a high R2 (0.93) and relatively low error metrics, but Gradient Boosting is slightly superior. Linear Regression performs poorly with a negative R2, suggesting it's a bad fit, while SVR and KNN show moderate performance but are significantly less accurate than the tree-based models.