Descriptive and Inferential Analysis

The original dataset used for this EDA was founded on Kaggle

After working through the dataset, I created a script to scrape esrb.org to increase the size of the data from 1900 rows to 12k rows.

Definitions

- E = Everyone
- ET = Everyone 10+
- T = Teen
- M = Mature

Console:

- 0 = Playstation 4
- 1 = PS4 & Xbox One

The following are 0 = no, 1 = yes

- alcohol_reference = Reference to and/or images of alcoholic beverages.
- animated_blood = Discolored and/or unrealistic depictions of blood.
- blood = Depcitions of blood.
- blood_and_gore = Depictions of blood or the mutilation of body parts.
- cartoon_violence = Violent actions involving cartoon-like situations and characters. May include violence where a character is unharmed after the action has been inflicted.
- crude_humor = Depictions or dialogue involving vulgar antics, including "bathroom" humor.
- drug_reference = Reference to and/or images of illegal drugs.
- fantasy_violence = Violent actions of a fantasy nature, involving human or non-human characters in situations easily distinguishable from real life.
- intense_violence = Graphic and realistic-looking depictions of physical conflict. May involve extreme and/or realistic blood, gore, weapons, and depictions of human injury and death.
- language = Moderate use of profanity.
- lyrics = References to profanity, sexuality, violence, alcohol, or drug use in music.
- mature_humor = Depictions or dialogue involving "adult" humor, including sexual references.
- mild_blood = Some blood.
- mild_cartoon_violence = Some violent actions involving cartoon.
- mild_fantasy_violence = Some violent actions of a fantasy nature.
- mild_language = Mild to moderate use of profanity.
- mild_lyrics = Mild References to profanity, sexuality, violence, alcohol, or drug use in music.
- mild_suggestive_themes = some provocative references or materials.
- mild_violence = Some scenes involving aggressive conflict.
- no_descriptors = No content descriptors.

- nudity = Graphic or prolonged depictions of nudity.
- partial_nudity = Brief and/or mild depictions of nudity.
- sexual_content = Non-explicit depictions of sexual behavior, possibly including partial nudity.
- sexual_themes = References to sex or sexuality.
- simulated_gambling = Player can gamble without betting or wagering real cash or currency.
- strong_language = Explicit and/or frequent use of profanity.
- strong_sexual_content = Explicit and/or frequent depictions of sexual behavior, possibly including nudity.
- suggestive_themes = Provocative references or materials.
- use_of_alcohol = The consumption of alcoholic beverages.
- use_of_drugs_and_alcohol = The consumption of alcoholic and drugs beverages.
- violence = Scenes involving aggressive conflict. May contain bloodless dismemberment.

For more information you can go to the ESRB website

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot  as plt
import seaborn as sns
sns.set_theme(style="darkgrid")
```

In [3]:
```
df = pd.read_csv('data/esrb_ratings_scraped.csv')

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12000 entries, 0 to 11999
Data columns (total 30 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   title                     12000 non-null  object
 1   console                   12000 non-null  object
 2   alcohol_reference         12000 non-null  int64 
 3   animated_blood            12000 non-null  int64 
 4   blood                     12000 non-null  int64 
 5   blood_and_gore            12000 non-null  int64 
 6   cartoon_violence          12000 non-null  int64 
 7   crude_humor               12000 non-null  int64 
 8   drug_reference            12000 non-null  int64 
 9   fantasy_violence          12000 non-null  int64 
 10  intense_violence          12000 non-null  int64 
 11  language                  12000 non-null  int64 
 12  mild_blood                12000 non-null  int64 
 13  mild_cartoon_violence     12000 non-null  int64 
 14  mild_fantasy_violence     12000 non-null  int64 
 15  mild_language             12000 non-null  int64 
 16  mild_lyrics               12000 non-null  int64 
 17  mild_suggestive_themes    12000 non-null  int64 
 18  mild_violence             12000 non-null  int64 
 19  nudity                    12000 non-null  int64 
 20  sexual_content            12000 non-null  int64 
 21  sexual_themes             12000 non-null  int64 
 22  simulated_gambling        12000 non-null  int64 
 23  strong_language           12000 non-null  int64 
 24  strong_sexual_content     12000 non-null  int64 
 25  suggestive_themes         12000 non-null  int64 
 26  use_of_alcohol            12000 non-null  int64 
```

```
 27  use_of_drugs_and_alcohol  12000 non-null  int64
 28  violence                  12000 non-null  int64
 29  esrb_rating               12000 non-null  object
dtypes: int64(27), object(3)
memory usage: 2.7+ MB
```

Check for null values.

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
title                     0
console                   0
alcohol_reference         0
animated_blood            0
blood                     0
blood_and_gore            0
cartoon_violence          0
crude_humor               0
drug_reference            0
fantasy_violence          0
intense_violence          0
language                  0
mild_blood                0
mild_cartoon_violence     0
mild_fantasy_violence     0
mild_language             0
mild_lyrics               0
mild_suggestive_themes    0
mild_violence             0
nudity                    0
sexual_content            0
sexual_themes             0
simulated_gambling        0
strong_language           0
strong_sexual_content     0
suggestive_themes         0
use_of_alcohol            0
use_of_drugs_and_alcohol  0
violence                  0
esrb_rating               0
dtype: int64
```

Looks pretty clean, given that most columns are binary

In [5]:
```
df.head()
```

Out[5]:

	title	console	alcohol_reference	animated_blood	blood	blood_and_gore	cartoon_violence
0	Yars Rising	PlayStation 5, Nintendo Switch	0	1	0	0	0
1	STAR WARS™: Bounty Hunter™	PlayStation 5, Nintendo Switch, Xbox Series	0	0	0	0	0
2	Tomb Raider I-III Remastered	Xbox One, Xbox Series	0	0	1	0	0

	title	console	alcohol_reference	animated_blood	blood	blood_and_gore	cartoon_violence
	Starring Lara Croft						
3	Mad Bullets	Nintendo Switch	0	0	0	0	0
4	Raiden NOVA	PlayStation 5, Nintendo Switch	0	0	0	0	0

5 rows × 30 columns

Check which ratings are present in this dataset

In [6]:
```
df.esrb_rating.unique()
```

Out[6]:
```
array(['ET', 'T', 'E', 'M'], dtype=object)
```

Just check for duplicates, since this is a smaller dataset and don't want to make it smaller

In [7]:
```
df[df.duplicated()]
```

Out[7]:

	title	console	alcohol_reference	animated_blood	blood	blood_and_gore	cartoon_viole
10	Yars Rising	PlayStation 5, Nintendo Switch	0	1	0	0	
11	STAR WARS™: Bounty Hunter™	PlayStation 5, Nintendo Switch, Xbox Series	0	0	0	0	
12	Tomb Raider I-III Remastered Starring Lara Croft	Xbox One, Xbox Series	0	0	1	0	
13	Mad Bullets	Nintendo Switch	0	0	0	0	
14	Raiden NOVA	PlayStation 5, Nintendo Switch	0	0	0	0	
...	...	...	...	...	...	...	
11671	Hidden Mysteries: Titanic	Macintosh, Windows PC	0	0	0	0	
11760	Digger HD	PlayStation 3	0	0	0	0	

	title	console	alcohol_reference	animated_blood	blood	blood_and_gore	cartoon_viole
11927	First Class Flurry	Windows PC	1	0	0	0	
11947	G.H.O.S.T. Chronicles: Phantom of the Faire	Windows PC	0	0	0	0	
11949	Mystery Legends: Sleepy Hollow	Windows PC	0	0	0	0	

174 rows × 30 columns

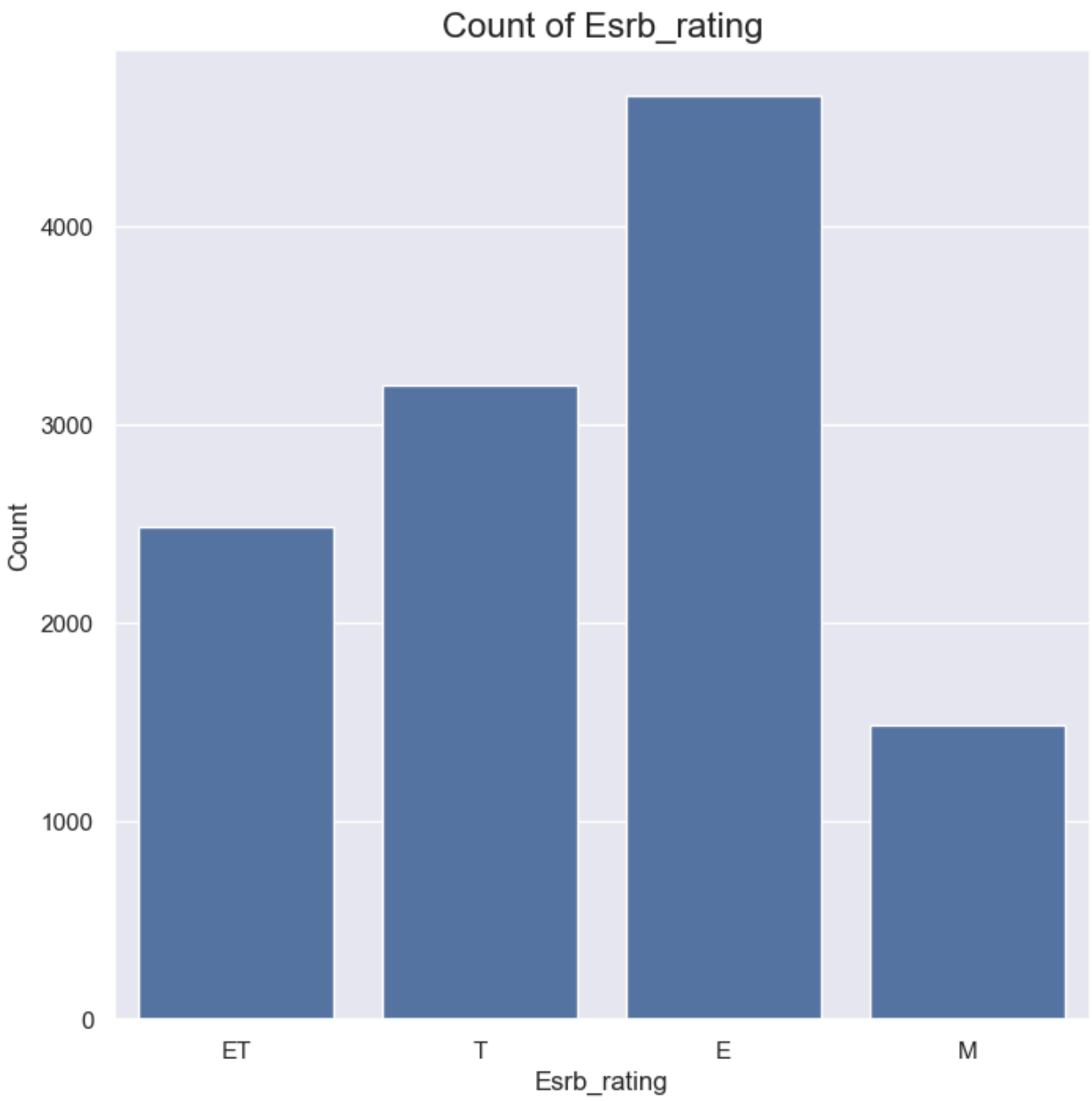
In [8]:
```
df = df.drop_duplicates(keep='first')
```

In [9]:
```
# create a function for making countplot graphs
def plot_counts(x, data):
    plt.figure(figsize=(8,8))
    sns.countplot(x=x, data=data)

    # Adding title and labels
    plt.title(f'Count of {x.capitalize()}', fontsize=16)
    plt.xlabel(f'{x.capitalize()}', fontsize=12)
    plt.ylabel('Count', fontsize=12)

    plt.show()
```

Descriptive Analysis

What are the ratings represented in this dataset?

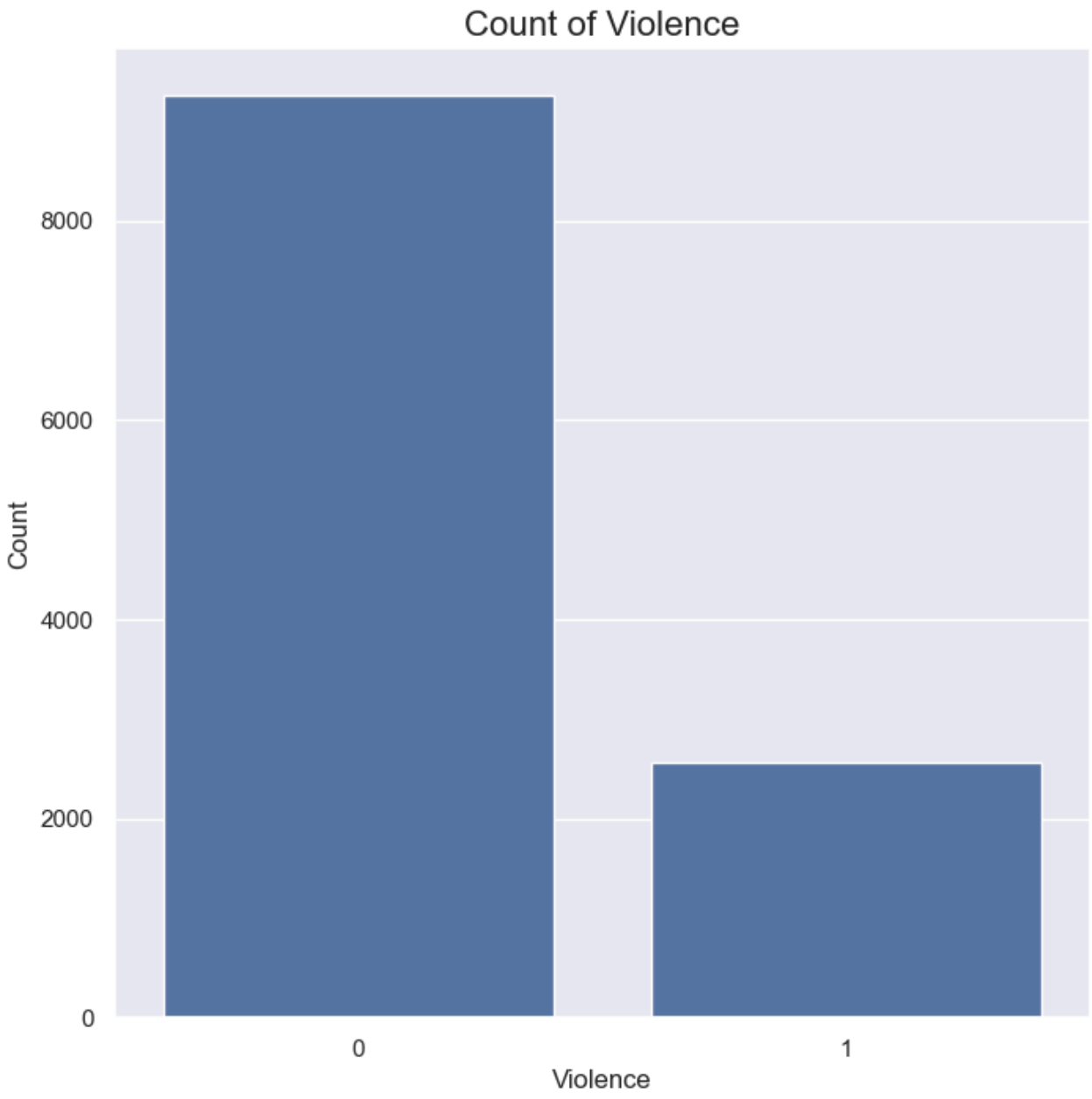
In [10]:
```
plot_counts('esrb_rating', df)
```



Mostly Everyone rated games.

How many violent video games are present in the dataset?

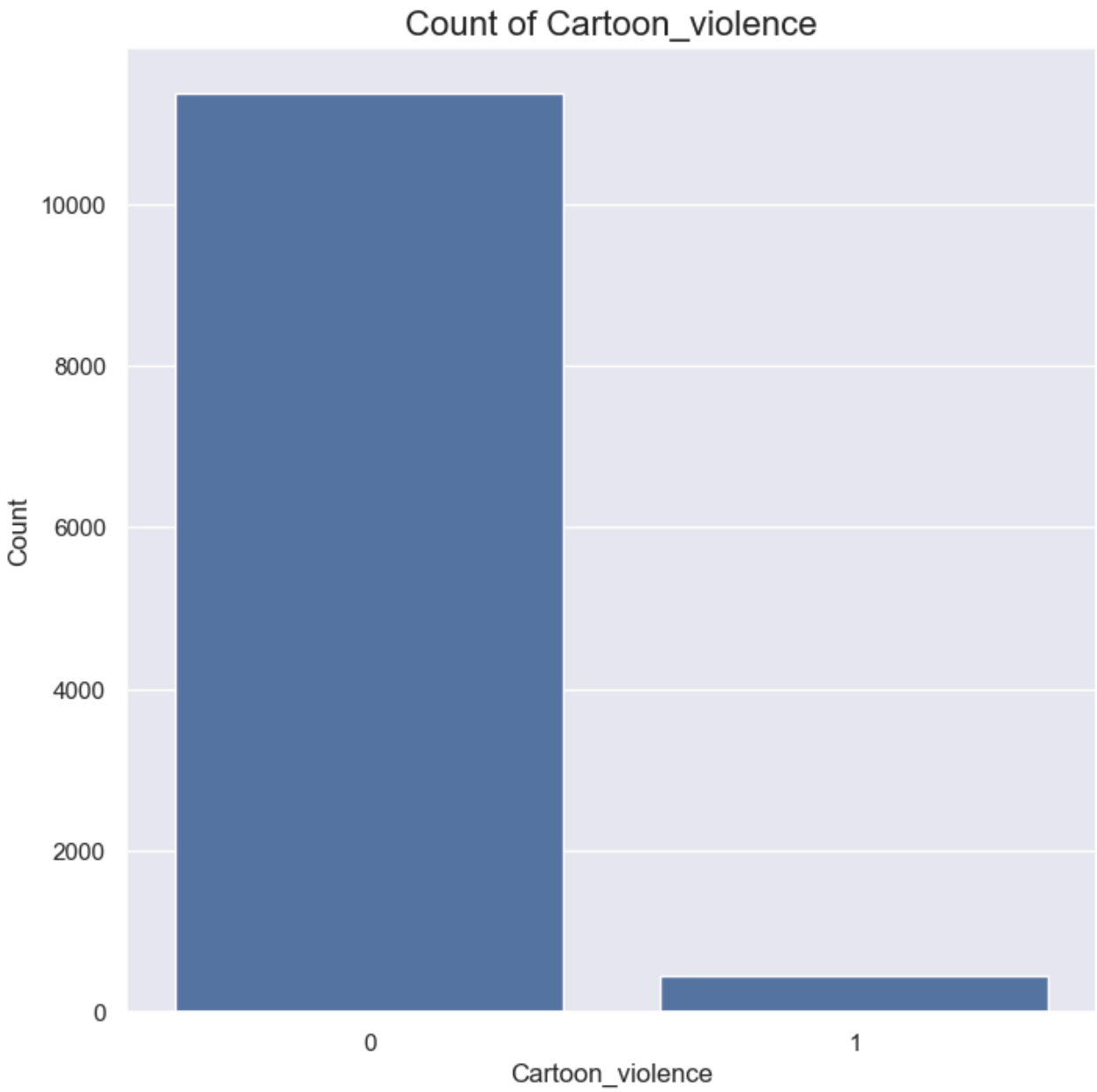
In [11]:
```
plot_counts('violence', df)
```



Let's check other types of violence

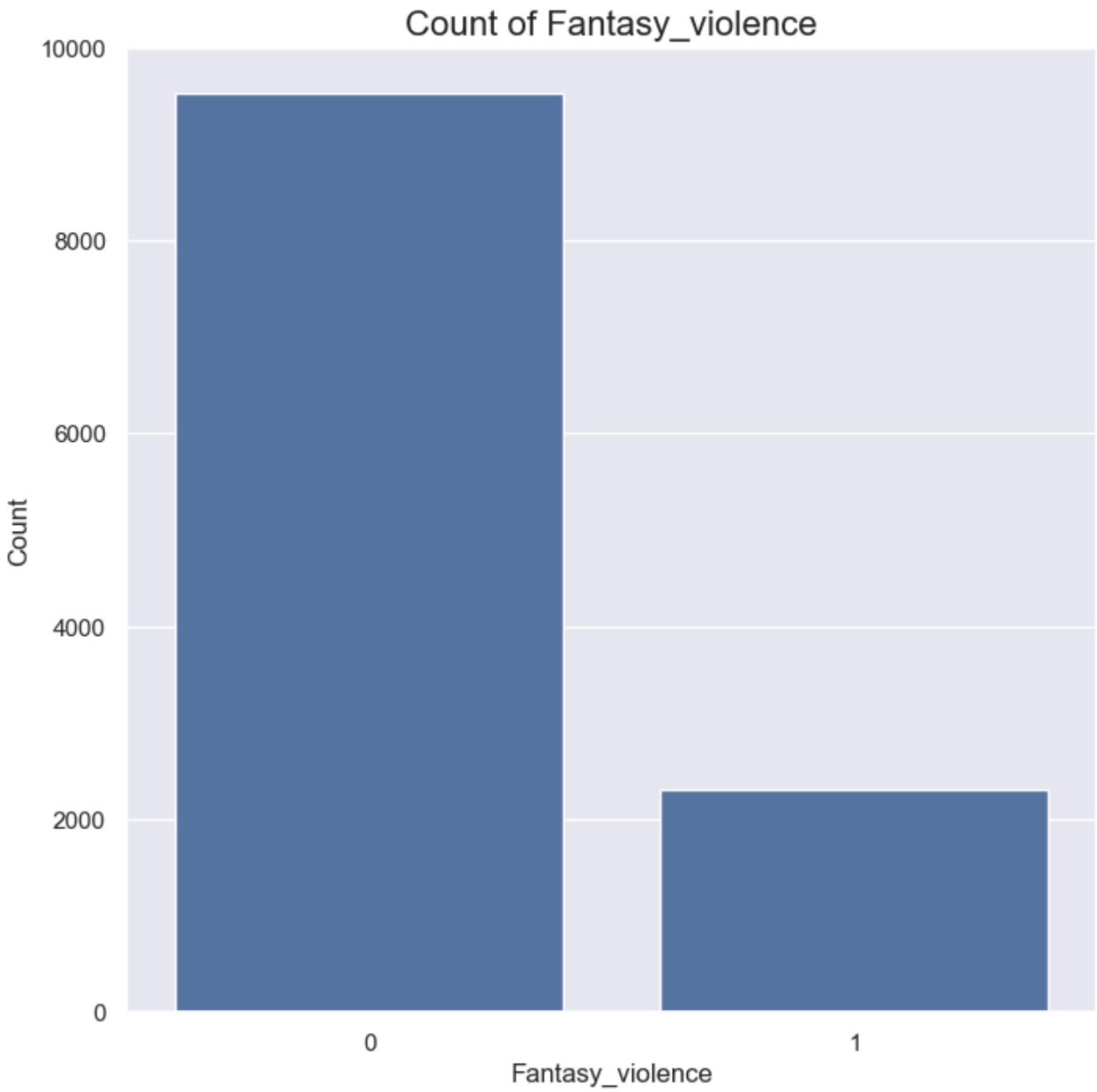
How many games contain cartoon violence?

In [12]:
```
plot_counts('cartoon_violence', df)
```



How many games contain fantasy violence?

In [13]:
```
plot_counts('fantasy_violence', df)
```

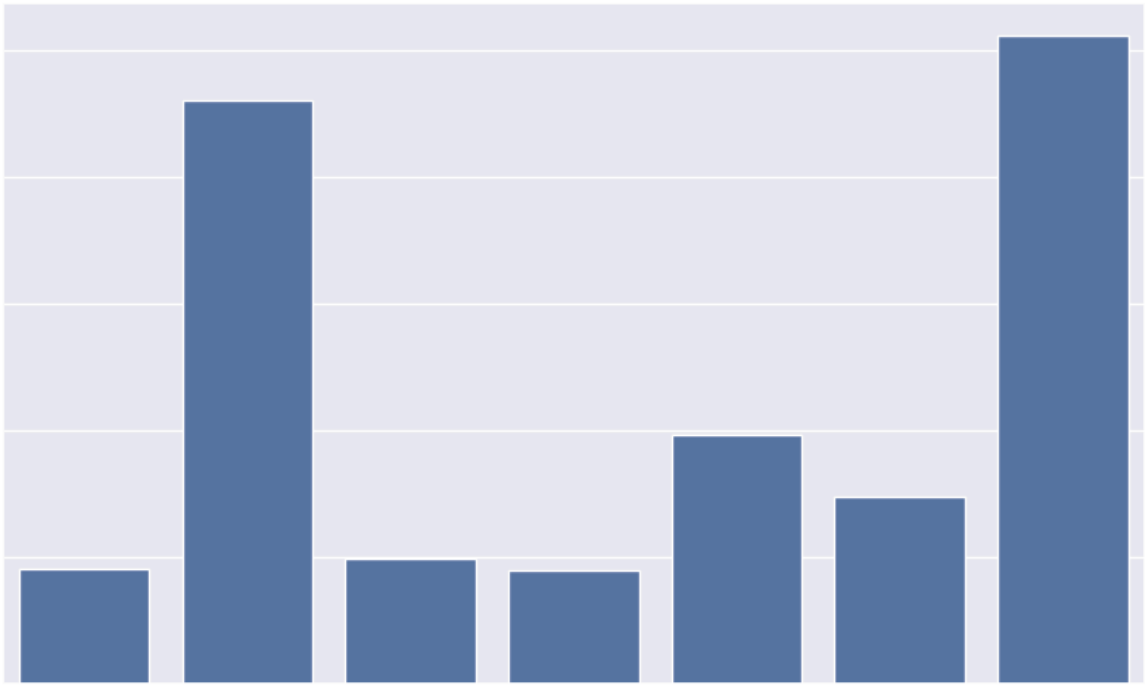


So Violence is categorized differently throughout all the games. It might be good to show all violence categories to get a full count.

How is violence represented throughout entire dataset?

In [41]:
```
# Step 1: Select columns containing the word 'violence'
violence_columns = df.filter(like='violence')

# Step 2: Aggregate the values by summing up rows (or choose another aggregation method
# If you want the sum of each column:
violence_aggregated = violence_columns.sum()

# Step 3: Plot the aggregated data
plt.figure(figsize=(10, 6))
sns.barplot(x=violence_aggregated.index, y=violence_aggregated.values)

# Adding title and labels
plt.title('Aggregated Values of Violence-related Columns', fontsize=16, color='white')
plt.xlabel('Violence Columns', fontsize=12, color='white')
```

```
plt.ylabel('Sum of Values', fontsize=12, color='white')

# Rotate x labels for better readability if necessary
plt.xticks(rotation=45, color='white')
plt.yticks(color='white')

plt.savefig('graphs/violence_columns.png', bbox_inches = 'tight', edgecolor='w', transp
# Display the plot
plt.show()
```



In [15]:
```
total_violence_count = violence_columns.sum().sum() #get sum for each column and then t

print(f"Total count across all 'violence' columns: {total_violence_count}")
```

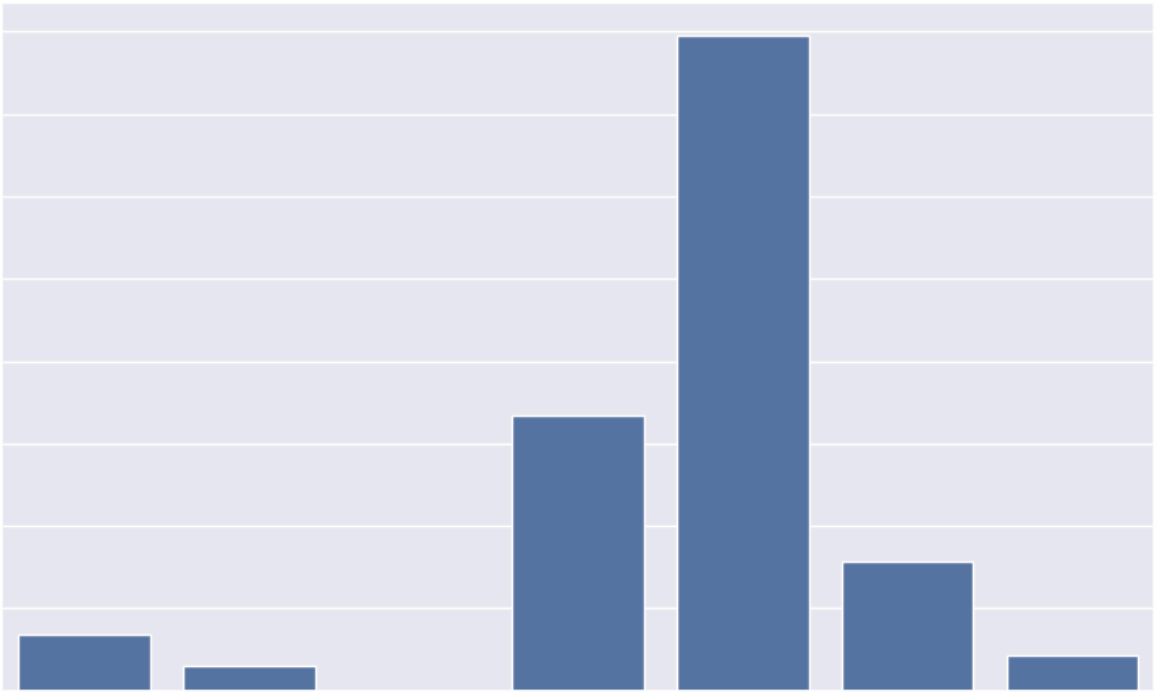
```
Total count across all 'violence' columns: 7973
```

Now that number makes a lot more sense for violence throughout all games in this dataset.

Do E rated games contain any types of violence?

In [42]:
```
# Filter rows where the 'esrb_ratings' column is 'E'
e_rated_games = df[df['esrb_rating'] == 'E']

# Select columns containing the word 'violence'
violence_columns = e_rated_games.filter(like='violence')

# Step 3: Count how many E-rated games have non-zero values in each violence-related co
violence_counts = (violence_columns > 0).sum()
```

```
# Step 4: Plot the results
plt.figure(figsize=(10, 6))
sns.barplot(x=violence_counts.index, y=violence_counts.values)

# Adding title and labels
plt.title('Number of E-Rated Games with Values in Violence-Related Columns', fontsize=1
plt.xlabel('Violence Columns', fontsize=12, color='white')
plt.ylabel('Count of E-Rated Games', fontsize=12, color='white')

# Rotate x labels for better readability if necessary
plt.xticks(rotation=45, color='white')
plt.yticks(color='white')

plt.savefig('graphs/violence_e_rated.png', bbox_inches = 'tight', edgecolor='w', transp
# Display the plot
plt.show()
```

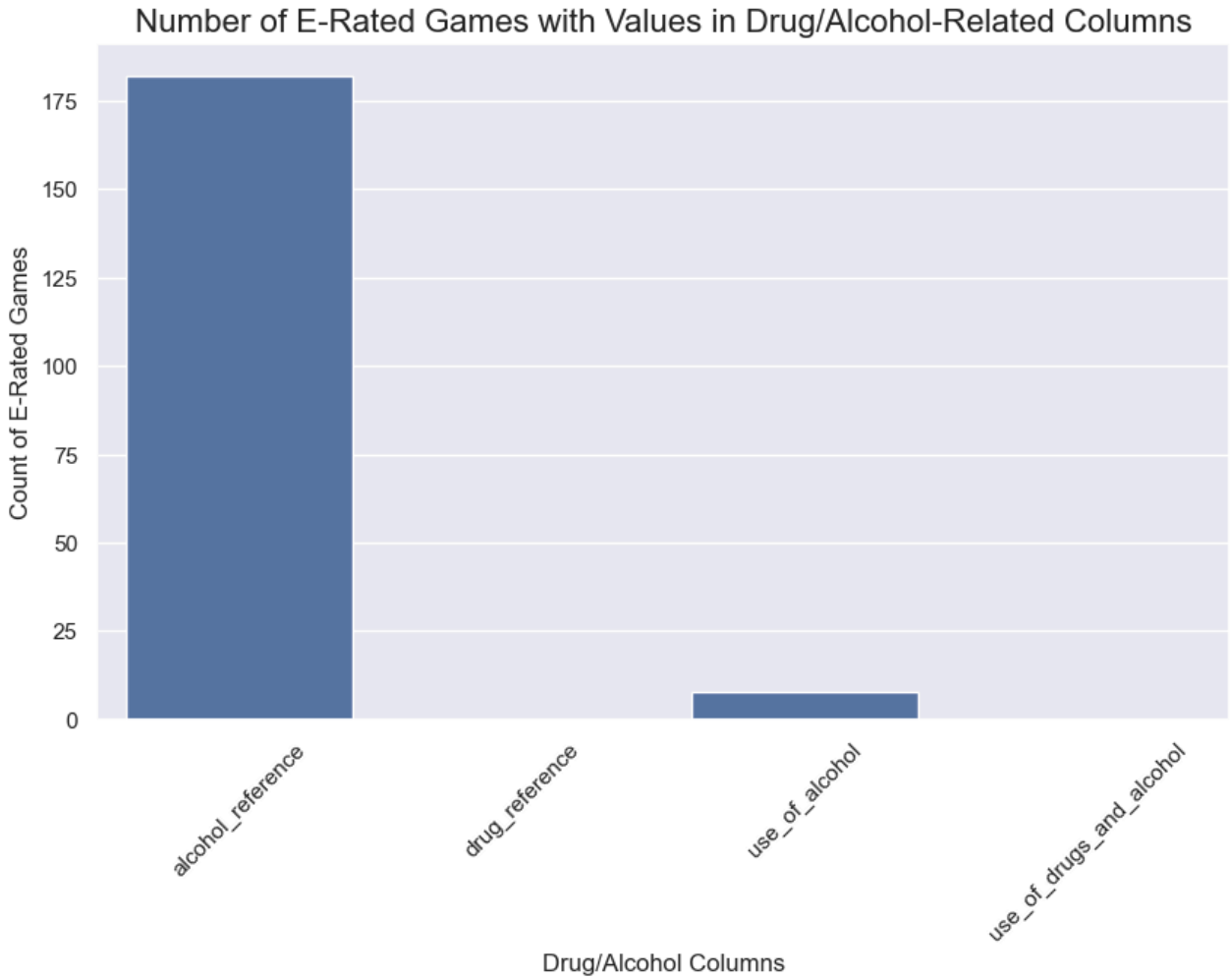


Are E rated games containing any drug or alcohol references?

In [17]:

```
# Filter columns containing the words 'drug' or 'alcohol'
drug_alcohol_columns = e_rated_games.filter(regex='drug|alcohol', axis=1)

# Step 2: Count how many E-rated games have non-zero values in each drug/alcohol-relate
drug_alcohol_counts = (drug_alcohol_columns > 0).sum()

# Step 3: Plot the results
plt.figure(figsize=(10, 6))
sns.barplot(x=drug_alcohol_counts.index, y=drug_alcohol_counts.values)
```

```
# Adding title and labels
plt.title('Number of E-Rated Games with Values in Drug/Alcohol-Related Columns', fontsi
plt.xlabel('Drug/Alcohol Columns', fontsize=12)
plt.ylabel('Count of E-Rated Games', fontsize=12)

# Rotate x labels for better readability if necessary
plt.xticks(rotation=45)

# Display the plot
plt.show()
```



In [18]:

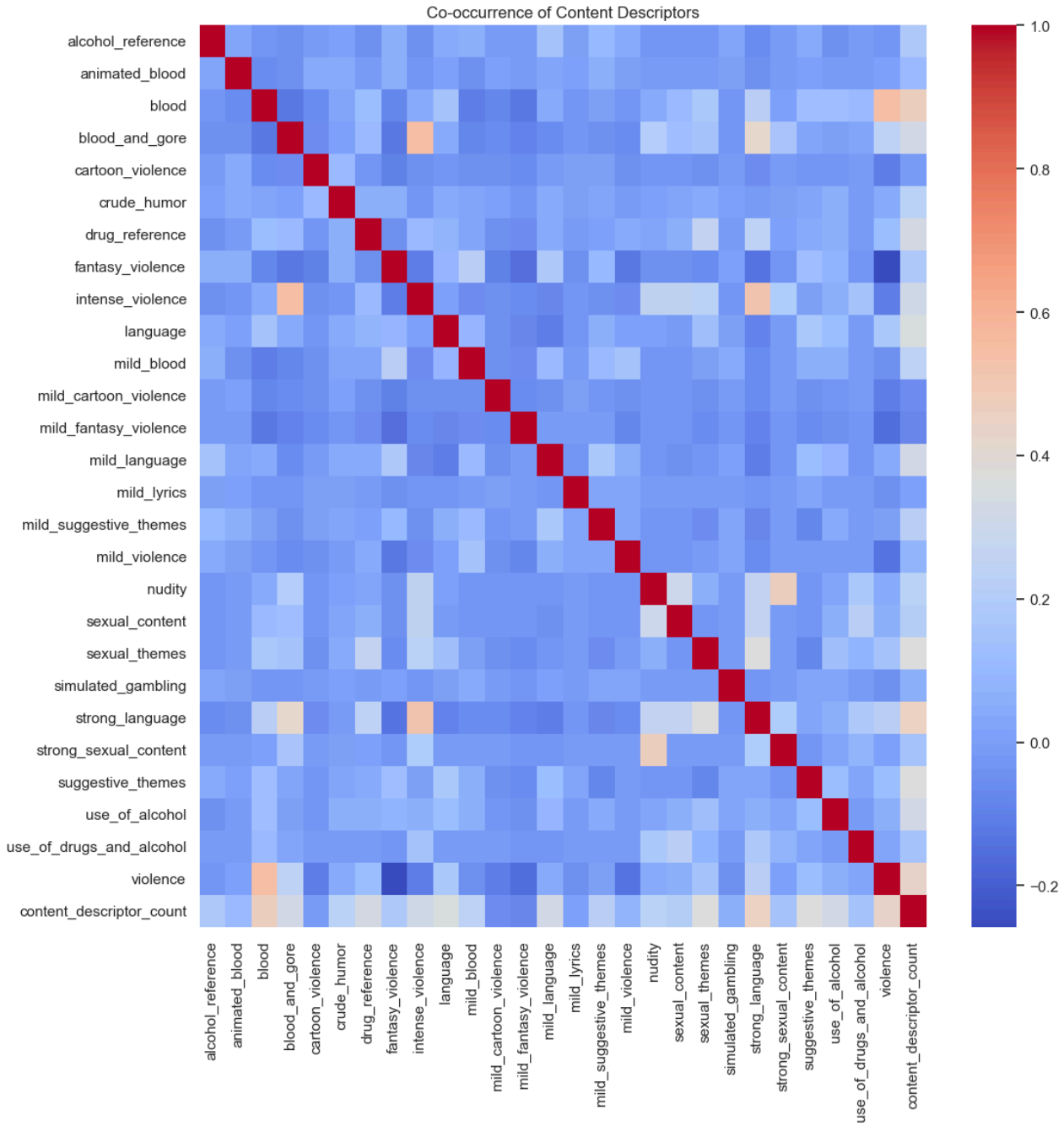
```
# Identify rows where any of the 'drug' or 'alcohol' columns have non-zero values
games_with_drug_or_alcohol = e_rated_games[drug_alcohol_columns.sum(axis=1) > 0]

# List the titles of those games
game_titles_with_drug_or_alcohol = games_with_drug_or_alcohol['title']

# Display the titles
if not game_titles_with_drug_or_alcohol.empty:
    print(f"Number of E-rated games with drug/alcohol-related content: {len(game_titles
    print(game_titles_with_drug_or_alcohol)
else:
    print("No E-rated games with drug/alcohol-related content found.")
```

```
Number of E-rated games with drug/alcohol-related content: 190
53                            Harvest Days
137      Hidden Objects 6: Shopping Clutter
```

```
471                              Backbeat
506                               Exo One
521                   Everybody 1-2-Switch!
                        ...
11868                          Mysteryville
11901                   THINK Logic Trainer
11906                   THINK Logic Trainer
11932                             Cook Wars
11990                    The Price is Right
Name: title, Length: 190, dtype: object
```

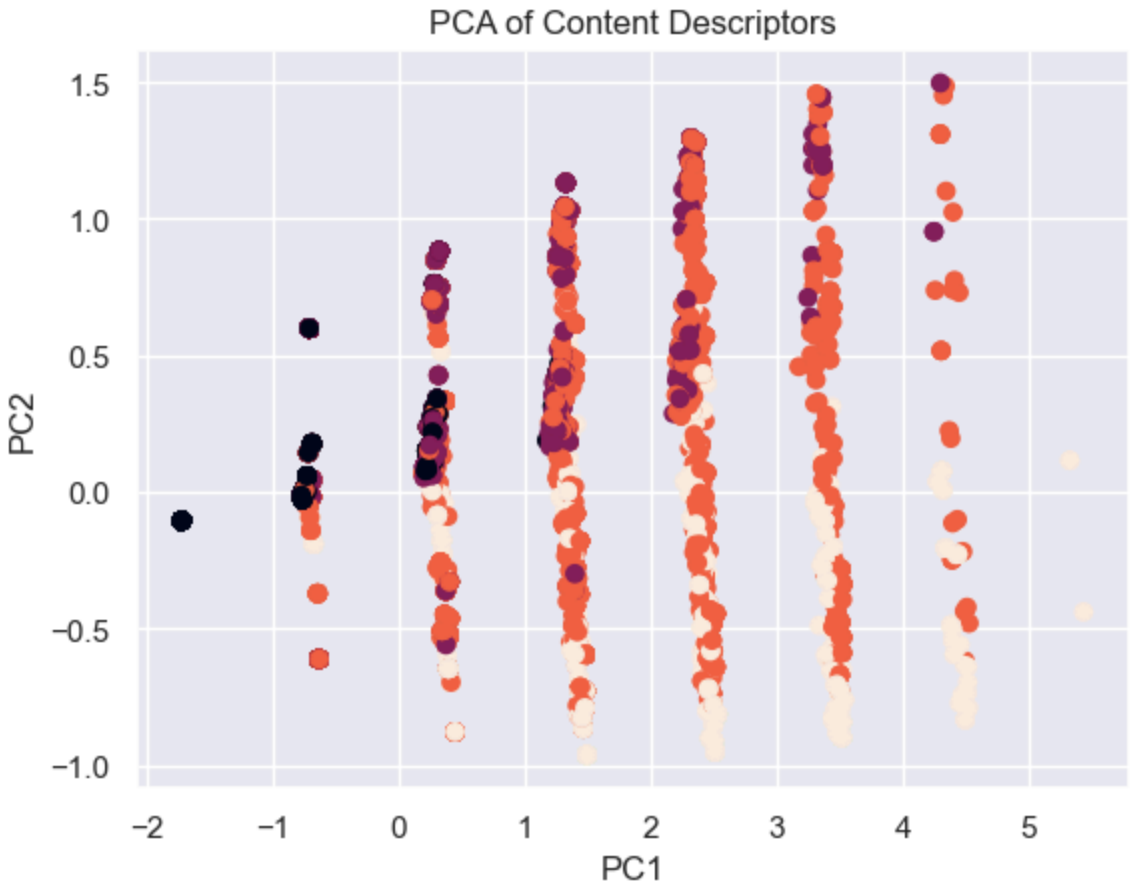
How often do two different content descriptors co-occur?

In [36]:
```
content_descriptor_columns = df.columns.drop(['title', 'console', 'esrb_rating'])

# Calculate correlation matrix (or co-occurrence)
co_occurrence_matrix = df[content_descriptor_columns].corr()

# Plot heatmap
plt.figure(figsize=(12, 12))
sns.heatmap(co_occurrence_matrix, annot=False, cmap='coolwarm')
plt.title('Co-occurrence of Content Descriptors')

plt.savefig('graphs/co-occurences_descriptors.png', bbox_inches = 'tight', edgecolor='w
plt.show()
```



Some of these definitely make sense. Violence with Blood, Strong Language with Intense Violence.

In [33]:
```
from sklearn.decomposition import PCA

# Perform PCA to reduce dimensions to 2D for visualization
pca = PCA(n_components=2)
pca_result = pca.fit_transform(df[content_descriptor_columns])

# Scatter plot of PCA results
plt.scatter(pca_result[:, 0], pca_result[:, 1], c=df['esrb_rating'].apply(lambda x: {'E
plt.title('PCA of Content Descriptors')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.show()
```



This might be useful in the modeling notebook to improve accuracy.

Inferential Analysis

In [19]:
```
from scipy.stats import chi2_contingency
from scipy.stats import f_oneway
```

Do games that feature animated blood have a higher probability of receiving an "M" (Mature) rating than games that do not?

Null Hypothesis (H0): There is no association between content descriptors (e.g., animated blood) and the ESRB rating.\ Alternative Hypothesis (HA): There is an association between content descriptors and the ESRB rating.

In [20]:
```
# significance level
alpha = 0.05

# Create a contingency table for 'animated_blood' and 'esrb_rating'
contingency_table = pd.crosstab(df['animated_blood'], df['esrb_rating'])

# Run the Chi-Square test
chi2, p, dof, expected = chi2_contingency(contingency_table)

# Display the test results
print(f"Chi-Square Statistic: {chi2}")
```

```
print(f"P-Value: {p}")

# Interpretation: If p-value < 0.05, reject the null hypothesis
if p < alpha:
    print("Reject the Null: There is a significant association between animated_blood a
else:
    print("Unable to reject the null")
```

```
Chi-Square Statistic: 200.7424399534661
P-Value: 2.9156822030262875e-43
Reject the Null: There is a significant association between animated_blood and esrb_rati
ng.
```

Is there a significant difference in the mean number of content descriptors across different ESRB ratings?

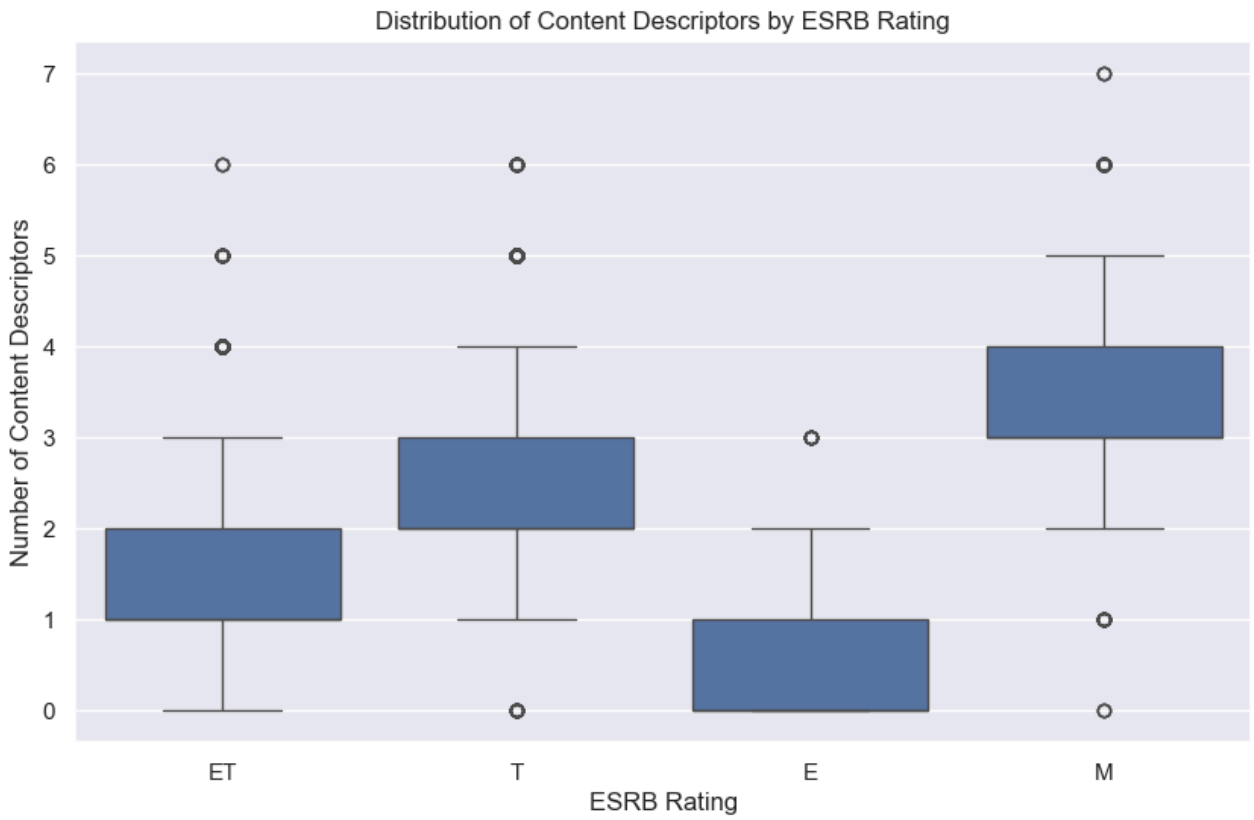
Null Hypothesis (H0): The mean number of content descriptors is the same for all ESRB rating categories.\ Alternative Hypothesis (HA): At least one ESRB rating category has a mean number of content descriptors that is different from the others.

In [21]:
```
# significance level
alpha = 0.05

# Calculate the number of content descriptors by summing relevant columns
content_descriptor_columns = df.columns.drop(['title', 'console', 'esrb_rating'])
df['content_descriptor_count'] = df[content_descriptor_columns].sum(axis=1)

# Group the content descriptor counts by ESRB rating
grouped_data = [df[df['esrb_rating'] == rating]['content_descriptor_count'] for rating

# Perform ANOVA test
f_stat, p_value = f_oneway(*grouped_data)

# Display the results
print(f"F-Statistic: {f_stat}")
print(f"P-Value: {p_value}")

# Interpretation
if p_value < alpha:
    print("Reject the Null: There is a significant difference in the mean number of con
else:
    print("Unable to reject the null")
```

```
F-Statistic: 5854.434968357328
P-Value: 0.0
Reject the Null: There is a significant difference in the mean number of content descrip
tors across ESRB ratings.
```

In [22]:
```
# Set the size of the plot
plt.figure(figsize=(10, 6))

# Create a boxplot to visualize the distribution of content descriptors by ESRB rating
sns.boxplot(x='esrb_rating', y='content_descriptor_count', data=df)

# Set plot labels and title
plt.title('Distribution of Content Descriptors by ESRB Rating')
plt.xlabel('ESRB Rating')
plt.ylabel('Number of Content Descriptors')
```

```
# Show the plot
plt.show()
```



This graph makes sense in how these should be distributed. The only issue that might arise is how some ET games have an amount of descriptors close to Teen rated. Also, Some of the Mature games have pretty few descriptors. This could be because the descriptor itself is a big one.

Let's just check to see if there is a significant difference between ET and T

In [24]:

```
# Significance level
alpha = 0.05

# Filter the dataframe for only 'ET' and 'T' ratings
df_filtered = df[df['esrb_rating'].isin(['ET', 'T'])].copy()

# Calculate the number of content descriptors by summing relevant columns
content_descriptor_columns = df_filtered.columns.drop(['title', 'console', 'esrb_rating
df_filtered['content_descriptor_count'] = df_filtered[content_descriptor_columns].sum(a

# Group the content descriptor counts by ESRB rating (only 'ET' and 'T')
grouped_data = [df_filtered[df_filtered['esrb_rating'] == rating]['content_descriptor_c

# Perform ANOVA test
f_stat, p_value = f_oneway(*grouped_data)

# Display the results
print(f"F-Statistic: {f_stat}")
print(f"P-Value: {p_value}")

# Interpretation
if p_value < alpha:
```

```
    print("Reject the Null: There is a significant difference in the mean number of con
else:
    print("Unable to reject the null: No significant difference between ET and T rating
```

```
F-Statistic: 1024.79627472666
P-Value: 7.021119827754624e-207
Reject the Null: There is a significant difference in the mean number of content descrip
tors between ET and T ratings.
```

So there is still a pretty strong significance between these two rating types.

Summary

In trying to better understand the rating system we focused on violence and drugs/alcohol. The hope here was to get an idea of how violence was categorized and how that spread was associated through all ratings.

It was unfortunate to find any drug/alcohol references in Everyone rated games, but the percentage of occurences to the games in the dataset was very low.

Luckily there was a significance found with animated blood and mature rating games. I would hope that aligned there because we want to make sure that these ratings are doing a good job of distinguishing themselves from another one.

There is another focus on how significant the difference in between the mean of descriptors between each rating. We continued to find a significance here. I wanted to dig deeper since the E10+ rating and the Teen rating seemed to overlap a bit. Fortunately, there still remained a significant difference between the two. We will use this information moving forward into our modeling notebook.