🌟 Simplified Bias-Free News Summarization Using Transformer Models 🌟

Notebook 1: Data Prep and EDA

Goal: Get our text data squeaky clean for NLP!

1. Load the Data

- Load `allsides_balanced_news_headlines-texts.csv` and `suggestions.csv`.
- Check for missing values, duplicates, and label imbalances.

2. NLP Cleaning

- **Tokenize:** Split text into words.
- **Remove Stopwords:** Ditch those pesky "the"s and "and"s.
- **Lemmatize:** Get those words back to their roots (running → run).
- **NER:** Find and tag names, places, and organizations.
- **POS Tagging:** Label each word with its part of speech.

3. Feature Engineering

- **TF-IDF:** Calculate those important word scores.
- **Sentiment Analysis:** Is it happy, sad, or angry?
- **Topic Modeling (LDA):** Uncover the hidden topics in our data.

4. EDA Time!

- **Visualize:** Check out the distribution of those bias labels.
- **Keywords:** What are the top words for each bias?
- **Search Trends:** Plot how those search suggestions change over time.

5. Save the Results

- Save our cleaned and prepped data as `preprocessed_articles.csv`.

Ready for some modeling!

About the Data

This project uses two main datasets:

1. `allsides_balanced_news_headlines-texts.csv`

- **Source:** AllSides (scraped Nov 2022)
- **Content:** ~22k news articles with bias labels (left, right, center).
  - Articles were hand-picked by experts to represent different viewpoints.
  - Includes headlines, full text, topics, and source outlets.
- **Goal:** Provides a balanced dataset to study media bias.

2. `suggestions.csv`

- **Source:** Google and Bing search suggestions.
- **Content:** ~670k search suggestions related to topics from the news articles.
  - Includes the original search term, suggested queries, and their ranking.
- **Goal:** Explore how search engines might reflect or influence bias.

🔹 General Importations

Let's start by importing everything we'll need for today's exercise.

In [7]:
```
# General Data Science Dependencies
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Regular Expression Parsing and Word Cloud Mapping
import re, wordcloud

# Natural Language Toolkit
import nltk; nltk.download("stopwords"); nltk.download("wordnet"); nltk.dowr

# Language Token Processing and Frequency Distribution Calculator
from textblob import Word
from collections import Counter

# Generalized Machine/Deep Learning Codependencies
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix, accurac

# TensorFlow for Deep Learning
import tensorflow as tf

import warnings
warnings.simplefilter(action='ignore', category=pd.errors.PerformanceWarning
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data] Downloading package omw-1.4 to /root/nltk_data...
```

🔹 Deep Learning Functional Initializations

As good practice, let's initialize the specific tools we'll be using from `TensorFlow` to make things a little more readable moving forward.

In [8]:

```
# Stopwords: Generally Recognized Noisy Terms
STOPWORDS = nltk.corpus.stopwords

# Sequential Model Architecture
Sequential = tf.keras.models.Sequential

# Connective Layers with Dropout
Dense = tf.keras.layers.Dense
Dropout = tf.keras.layers.Dropout

# Early Stopping Optimization
EarlyStopping = tf.keras.callbacks.EarlyStopping

# Natural Text-Based Language Processing Layers with RNN
Embedding = tf.keras.layers.Embedding
LSTM = tf.keras.layers.LSTM
SpatialDropout1D = tf.keras.layers.SpatialDropout1D

# Language Tokenization Filter
Tokenizer = tf.keras.preprocessing.text.Tokenizer

# Padding Function for Dataset Ingestion Preprocessing
pad_sequences = tf.keras.preprocessing.sequence.pad_sequences
```

🔹 Data Loading and Preprocessing

Let's first load and take a look at what data we're working with.

In [9]:

```
# Load the datasets
try:
    articles_df = pd.read_csv('/content/drive/MyDrive/Data/Qbias/allsides_ba
    suggestions_df = pd.read_csv('/content/drive/MyDrive/Data/Qbias/suggesti
    print("Datasets loaded successfully!")
except FileNotFoundError:
    print("Error: One or both of the CSV files were not found. Please uploac
    # Handle the error appropriately, e.g., exit the script or prompt the us
```

```
Datasets loaded successfully!
```

In [10]:

```
# Display the first few rows of both datasets for inspection
articles_df.head()
```

Out[10]:

	Unnamed: 0	title	tags	heading	source	text	bias_ra
0	0	Gun Violence Over Fourth of July Weekend	['Protests', 'Fourth Of July', 'Gun Control An...	Chicago Gun Violence Spikes and Increasingly F...	New York Times (News)	As Yasmin Miller drove home from a laundromat ...	
1	1	Gun Violence Over Fourth of July Weekend	['Protests', 'Fourth Of July', 'Gun Control An...	‘Bullets just came from nowhere’: Fourth of Ju...	Chicago Tribune	As many Chicagoans were celebrating the Fourth...	c
2	2	Gun Violence Over Fourth of July Weekend	['Protests', 'Fourth Of July', 'Gun Control An...	Dozens of shootings across US mark bloody July...	New York Post (News)	The nation’s 4th of July weekend was marred by...	
3	3	Yellen Warns Congress of 'Economic Recession' ...	['Janet Yellen', 'Debt Ceiling', 'Economic Pol...	Federal Government Will Run Out of Cash on Oct...	The Epoch Times	Treasury Secretary Janet Yellen on Tuesday war...	
4	4	Yellen Warns Congress of 'Economic Recession' ...	['Janet Yellen', 'Debt Ceiling', 'Economic Pol...	Yellen tells Congress that U.S. will run out o...	Washington Post	Treasury Secretary Janet Yellen on Tuesday tol...	

In [11]:

```
suggestions_df.head()
```

Out[11]:

	Unnamed: 0	query_input	query_suggestion	rank	search_engine	date
0	0	Madeline Albright	madeleine albright	1	google	2022- 13:43:00.51
1	1	Madeline Albright	madeleine albright frasi	2	google	2022- 13:43:00.51
2	2	Madeline Albright	madeleine albright una mamma per amica	3	google	2022- 13:43:00.51
3	3	Madeline Albright	madeleine albright bambini	4	google	2022- 13:43:00.51
4	4	Madeline Albright	madeleine albright frasi celebri	5	google	2022- 13:43:00.51

🔹 Dataset Overview

We've loaded our two datasets. Here's a quick look at what we're working with:

1. `allsides_balanced_news_headlines-texts.csv`

Column	Description
`Unnamed: 0`	Index column
`title`	Article title
`tags`	Associated topics/themes
`heading`	Article headline
`source`	News source
`text`	Full article text
`bias_rating`	Bias label (left, right, center)

Example: Articles on gun violence, economic policy, labeled with their respective bias.

2. `suggestions.csv`

Column	Description
`Unnamed: 0`	Index column
`query_input`	Original search query
`query_suggestion`	Suggested query
`rank`	Suggestion ranking
`search_engine`	Search engine used (e.g., Google)
`datetime`	Search timestamp
`root_term`	Core search term
`location`	Search location

Example: Search suggestions related to topics like "Madeline Albright".

🔹 Next Steps

Alright, time to dive deeper into our data! Here's the plan:

1. Data Cleaning

- Hunt down those missing values, duplicates, and inconsistencies. 🕵️
- Summarize how those bias labels are distributed in the AllSides dataset.

2. NLP Preprocessing

- **Tokenize:** Split the text into individual words.
- **Stopword Removal:** Get rid of common words like "the" and "and".
- **Lemmatize:** Convert words to their base forms (e.g., "running" to "run").
- **NER:** Identify and tag entities like people, places, and organizations.
- **POS Tagging:** Figure out the part of speech for each word.

3. EDA & Visualization

- **Bias Distribution:** Visualize how those bias labels are spread out.
- **Keyword Frequencies:** What are the most common words for each bias?
- **Search Trends:** See how those search suggestions change over time.

Let's kick things off with some cleaning and get a handle on those key statistics! 🧹📊

In [12]:
```
articles_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21754 entries, 0 to 21753
Data columns (total 7 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   Unnamed: 0    21754 non-null  int64 
 1   title         21754 non-null  object
 2   tags          21754 non-null  object
 3   heading       21754 non-null  object
 4   source        21746 non-null  object
 5   text          21747 non-null  object
 6   bias_rating   21754 non-null  object
dtypes: int64(1), object(6)
memory usage: 1.2+ MB
```

In [13]:

```
articles_df.describe()
```

Out[13]:

	Unnamed: 0
count	21754.000000
mean	10876.500000
std	6279.983214
min	0.000000
25%	5438.250000
50%	10876.500000
75%	16314.750000
max	21753.000000

In [14]:

```
# Remove the unnamed column if it exists
if 'Unnamed: 0' in articles_df.columns:
    articles_df = articles_df.drop(columns=['Unnamed: 0'])

articles_df.head()
```

Out[14]:

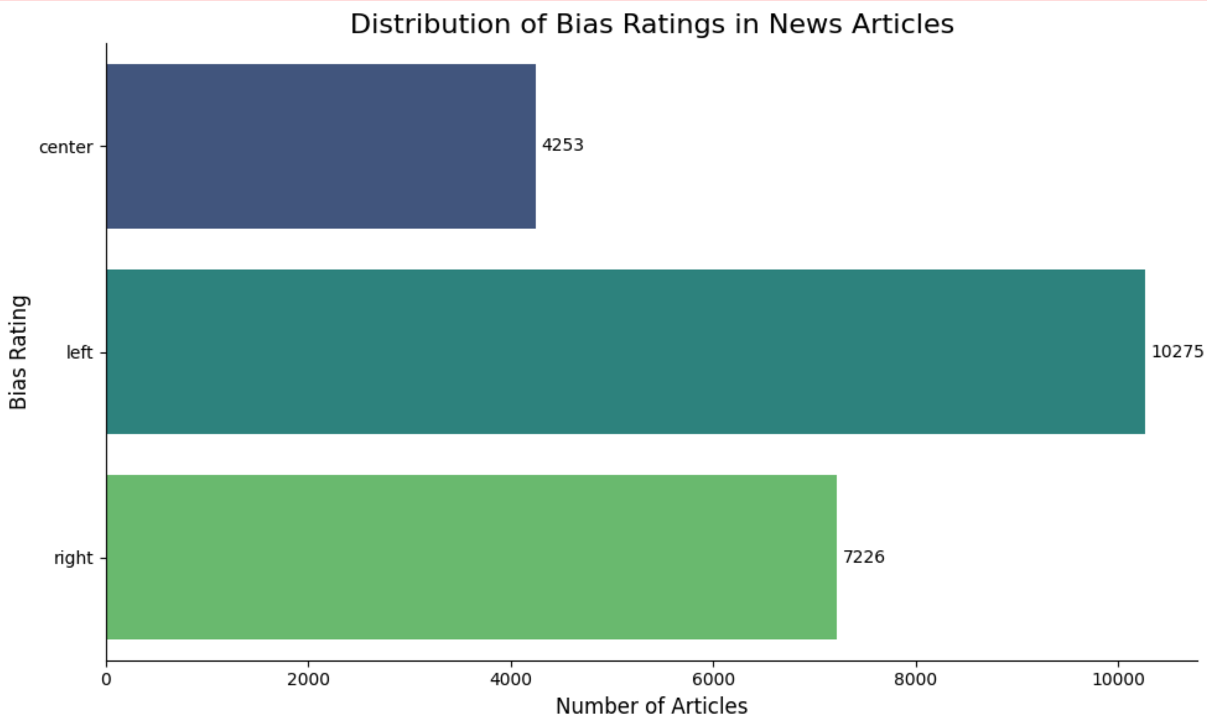
	title	tags	heading	source	text	bias_rating
0	Gun Violence Over Fourth of July Weekend	['Protests', 'Fourth Of July', 'Gun Control An...	Chicago Gun Violence Spikes and Increasingly F...	New York Times (News)	As Yasmin Miller drove home from a laundromat ...	left
1	Gun Violence Over Fourth of July Weekend	['Protests', 'Fourth Of July', 'Gun Control An...	‘Bullets just came from nowhere’: Fourth of Ju...	Chicago Tribune	As many Chicagoans were celebrating the Fourth...	center
2	Gun Violence Over Fourth of July Weekend	['Protests', 'Fourth Of July', 'Gun Control An...	Dozens of shootings across US mark bloody July...	New York Post (News)	The nation’s 4th of July weekend was marred by...	right
3	Yellen Warns Congress of 'Economic Recession' ...	['Janet Yellen', 'Debt Ceiling', 'Economic Pol...	Federal Government Will Run Out of Cash on Oct...	The Epoch Times	Treasury Secretary Janet Yellen on Tuesday war...	right
4	Yellen Warns Congress of 'Economic Recession' ...	['Janet Yellen', 'Debt Ceiling', 'Economic Pol...	Yellen tells Congress that U.S. will run out o...	Washington Post	Treasury Secretary Janet Yellen on Tuesday tol...	left

In [15]:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Group data and get counts
bias_counts = articles_df.groupby('bias_rating').size()

# Create the plot
plt.figure(figsize=(10, 6))  # Adjust figure size for better visibility
ax = sns.barplot(x=bias_counts.values, y=bias_counts.index, palette="viridis

# Add labels and title
plt.title('Distribution of Bias Ratings in News Articles', fontsize=16)
plt.xlabel('Number of Articles', fontsize=12)
plt.ylabel('Bias Rating', fontsize=12)

# Annotate bars with counts
for p in ax.patches:
    width = p.get_width()
    ax.text(width + 50,       # Position the text inside the bar
            p.get_y() + p.get_height() / 2,
```

```
                '{:1.0f}'.format(width),
                ha="left", va="center")

# Remove top and right spines for cleaner look
sns.despine()

plt.tight_layout()  # Adjust layout for better spacing
plt.show()
```

```
<ipython-input-15-925c3cb2455c>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed
in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the
same effect.

  ax = sns.barplot(x=bias_counts.values, y=bias_counts.index, palette="virid
is") # Use seaborn for better aesthetics and a different color palette
```



💡 Key Insights:

- The bar chart displays the number of articles in each bias category.
- The "Left" bias has the highest representation with 10,274 articles, followed by "Right" bias with 7,225 articles, and "Center" bias with 4,252 articles.
- This indicates a potential imbalance in the dataset, which could influence downstream analysis.

In [16]:
```
# Check for missing values and drop
print(articles_df.isnull().sum())
```

```
title          0
tags           0
heading        0
source         8
text           7
bias_rating    0
dtype: int64
```

In [17]:
```
# Drop rows with missing values in the 'text' and 'source' column
articles_df.dropna(subset=['text'], inplace=True)

# Verify if missing values are removed
print(articles_df.isnull().sum())
```

```
title          0
tags           0
heading        0
source         8
text           0
bias_rating    0
dtype: int64
```

In [18]:
```
articles_df.dropna(subset=['source'], inplace=True)

# Verify if missing values are removed
print(articles_df.isnull().sum())
```

```
title          0
tags           0
heading        0
source         0
text           0
bias_rating    0
dtype: int64
```

In [19]:
```
# Check for duplicate rows
print(f"Number of duplicate rows: {articles_df.duplicated().sum()}")
```

```
Number of duplicate rows: 3
```

In [20]:
```
# Drop duplicate rows
articles_df.drop_duplicates(inplace=True)

# Verify if duplicates are removed
print(f"Number of duplicate rows after removal: {articles_df.duplicated().su
```

```
Number of duplicate rows after removal: 0
```

In [21]:
```
# Convert text to lowercase
articles_df['text'] = articles_df['text'].str.lower()
```

In [22]:
```
# Remove punctuation
articles_df['text'] = articles_df['text'].apply(lambda x: re.sub(r'[^\w\s]',
```

In [23]:
```
# Remove numbers
articles_df['text'] = articles_df['text'].str.replace('\d+', '')
```

In [24]:
```
# Remove extra whitespace
articles_df['text'] = articles_df['text'].apply(lambda x: ' '.join(x.split()
```

In [25]:
```
import nltk

nltk.download('punkt_tab')

# Your existing code to tokenize:
articles_df['tokens'] = articles_df['text'].apply(lambda x: nltk.word_tokeni
```

```
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt_tab.zip.
```

In [26]:
```
# Remove stopwords
stop_words = STOPWORDS.words('english')
stop_words.extend(['said'])  # Add 'said' to the stopwords list
articles_df['tokens'] = articles_df['tokens'].apply(lambda x: [word for word

# Lemmatize
articles_df['tokens'] = articles_df['tokens'].apply(lambda x: [Word(word).le

# Join tokens back into text
articles_df['cleaned_text'] = articles_df['tokens'].apply(lambda x: ' '.join

#Drop the original text and tokens column
articles_df = articles_df.drop(columns=['text', 'tokens'])

#Display the first 5 rows
articles_df.head()
```

Out[26]:

	title	tags	heading	source	bias_rating	cleaned_text
0	Gun Violence Over Fourth of July Weekend	['Protests', 'Fourth Of July', 'Gun Control An...	Chicago Gun Violence Spikes and Increasingly F...	New York Times (News)	left	yasmin miller drove home laundromat chicago en...
1	Gun Violence Over Fourth of July Weekend	['Protests', 'Fourth Of July', 'Gun Control An...	'Bullets just came from nowhere': Fourth of Ju...	Chicago Tribune	center	many chicagoans celebrating fourth july barbec...
2	Gun Violence Over Fourth of July Weekend	['Protests', 'Fourth Of July', 'Gun Control An...	Dozens of shootings across US mark bloody July...	New York Post (News)	right	nation 4th july weekend marred wrong kind fire...
3	Yellen Warns Congress of 'Economic Recession' ...	['Janet Yellen', 'Debt Ceiling', 'Economic Pol...	Federal Government Will Run Out of Cash on Oct...	The Epoch Times	right	treasury secretary janet yellen tuesday warned...
4	Yellen Warns Congress of 'Economic Recession' ...	['Janet Yellen', 'Debt Ceiling', 'Economic Pol...	Yellen tells Congress that U.S. will run out o...	Washington Post	left	treasury secretary janet yellen tuesday told c...

In [27]:

```
#Save the preprocessed data
articles_df.to_csv('/content/drive/MyDrive/Data/Qbias/preprocessed_articles.
```

In [28]:

```
suggestions_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 671669 entries, 0 to 671668
Data columns (total 8 columns):
 #   Column            Non-Null Count   Dtype 
---  ------            --------------   ----- 
 0   Unnamed: 0        671669 non-null  int64 
 1   query_input       671669 non-null  object
 2   query_suggestion  667211 non-null  object
 3   rank              671669 non-null  int64 
 4   search_engine     671669 non-null  object
 5   datetime          671669 non-null  object
 6   root_term         671669 non-null  object
 7   location          671669 non-null  object
dtypes: int64(2), object(6)
memory usage: 41.0+ MB
```

In [29]:
```
suggestions_df.describe()
```

Out[29]:

	Unnamed: 0	rank
count	671669.000000	671669.000000
mean	335834.000000	5.297941
std	193894.283315	2.870200
min	0.000000	1.000000
25%	167917.000000	3.000000
50%	335834.000000	5.000000
75%	503751.000000	8.000000
max	671668.000000	10.000000

In [30]:
```
# Drop the 'Unnamed: 0' column from suggestions_df if it exists
if 'Unnamed: 0' in suggestions_df.columns:
    suggestions_df = suggestions_df.drop(columns=['Unnamed: 0'])
```

In [31]:
```
# Check for missing values in suggestions_df
print(suggestions_df.isnull().sum())
```

```
query_input            0
query_suggestion    4458
rank                   0
search_engine          0
datetime               0
root_term              0
location               0
dtype: int64
```

In [32]:
```
# Drop rows with missing 'query_suggestion' values:
suggestions_df.dropna(subset=['query_suggestion'], inplace=True)

# After choosing a strategy, verify the result:
print(suggestions_df['query_suggestion'].isnull().sum())
```

```
0
```

In [33]:
```
# Check for duplicate rows in suggestions_df
print(f"Number of duplicate rows in suggestions_df: {suggestions_df.duplicat
```

```
Number of duplicate rows in suggestions_df: 0
```

In [34]:
```
# Convert 'query_input' and 'query_suggestion' to lowercase
suggestions_df['query_input'] = suggestions_df['query_input'].str.lower()
suggestions_df['query_suggestion'] = suggestions_df['query_suggestion'].str.

# Remove punctuation from 'query_input' and 'query_suggestion'
suggestions_df['query_input'] = suggestions_df['query_input'].apply(lambda x
suggestions_df['query_suggestion'] = suggestions_df['query_suggestion'].appl

# Remove numbers from 'query_input' and 'query_suggestion'
```

```python
suggestions_df['query_input'] = suggestions_df['query_input'].str.replace('\
suggestions_df['query_suggestion'] = suggestions_df['query_suggestion'].str.

# Remove extra whitespace from 'query_input' and 'query_suggestion'
suggestions_df['query_input'] = suggestions_df['query_input'].apply(lambda x
suggestions_df['query_suggestion'] = suggestions_df['query_suggestion'].appl

# Tokenize 'query_input' and 'query_suggestion'
suggestions_df['query_input_tokens'] = suggestions_df['query_input'].apply(l
suggestions_df['query_suggestion_tokens'] = suggestions_df['query_suggestion

# Remove stopwords
suggestions_df['query_input_tokens'] = suggestions_df['query_input_tokens'].
suggestions_df['query_suggestion_tokens'] = suggestions_df['query_suggestion

# Lemmatize
suggestions_df['query_input_tokens'] = suggestions_df['query_input_tokens'].
suggestions_df['query_suggestion_tokens'] = suggestions_df['query_suggestion

# Join tokens back into text
suggestions_df['cleaned_query_input'] = suggestions_df['query_input_tokens']
suggestions_df['cleaned_query_suggestion'] = suggestions_df['query_suggestio

# Drop the original text and tokens columns
suggestions_df = suggestions_df.drop(columns=['query_input', 'query_suggesti

# Display first 5 rows of cleaned suggestions_df
suggestions_df.head()
```

Out[34]:

	rank	search_engine	datetime	root_term	location	cleaned_query_in
0	1	google	2022-11-30 13:43:00.511519	Madeline Albright	['Council Bluffs', 'Iowa', 'United States']	madeline albr
1	2	google	2022-11-30 13:43:00.511519	Madeline Albright	['Council Bluffs', 'Iowa', 'United States']	madeline albr
2	3	google	2022-11-30 13:43:00.511519	Madeline Albright	['Council Bluffs', 'Iowa', 'United States']	madeline albr
3	4	google	2022-11-30 13:43:00.511519	Madeline Albright	['Council Bluffs', 'Iowa', 'United States']	madeline albr
4	5	google	2022-11-30 13:43:00.511519	Madeline Albright	['Council Bluffs', 'Iowa', 'United States']	madeline albr

In [35]:

```
# Save the cleaned suggestions_df to a new CSV file in your Google Drive
suggestions_df.to_csv('/content/drive/MyDrive/Data/Qbias/cleaned_suggestions
```

In [36]:

```
from textblob import TextBlob

# Function to perform sentiment analysis
def analyze_sentiment(text):
  analysis = TextBlob(text)
  return analysis.sentiment.polarity

# Apply sentiment analysis to articles_df
articles_df['sentiment'] = articles_df['cleaned_text'].apply(analyze_sentime

# Apply sentiment analysis to suggestions_df (both columns)
suggestions_df['query_input_sentiment'] = suggestions_df['cleaned_query_inpu
suggestions_df['query_suggestion_sentiment'] = suggestions_df['cleaned_query

# Display the first few rows with sentiment scores
print(articles_df.head())
print(suggestions_df.head())
```

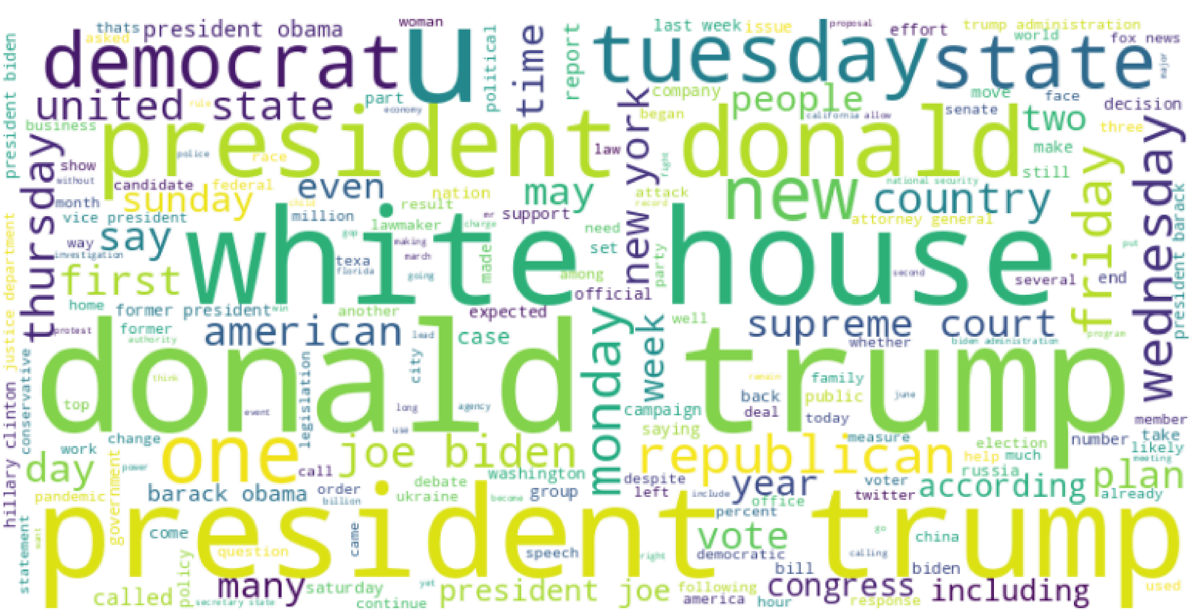
```
                                          title  \
0          Gun Violence Over Fourth of July Weekend
1          Gun Violence Over Fourth of July Weekend
2          Gun Violence Over Fourth of July Weekend
3  Yellen Warns Congress of 'Economic Recession' ...
4  Yellen Warns Congress of 'Economic Recession' ...

                                           tags  \
0  ['Protests', 'Fourth Of July', 'Gun Control An...
1  ['Protests', 'Fourth Of July', 'Gun Control An...
2  ['Protests', 'Fourth Of July', 'Gun Control An...
3  ['Janet Yellen', 'Debt Ceiling', 'Economic Pol...
4  ['Janet Yellen', 'Debt Ceiling', 'Economic Pol...

                                        heading                 source
\
0  Chicago Gun Violence Spikes and Increasingly F...  New York Times (News)
1  ‘Bullets just came from nowhere’: Fourth of Ju...        Chicago Tribune
2  Dozens of shootings across US mark bloody July...   New York Post (News)
3  Federal Government Will Run Out of Cash on Oct...        The Epoch Times
4  Yellen tells Congress that U.S. will run out o...        Washington Post

  bias_rating                                       cleaned_text  sentiment
0        left  yasmin miller drove home laundromat chicago en...   0.122727
1      center  many chicagoans celebrating fourth july barbec...  -0.200000
2       right  nation 4th july weekend marred wrong kind fire...  -0.017500
3       right  treasury secretary janet yellen tuesday warned...   0.057738
4        left  treasury secretary janet yellen tuesday told c...  -0.015152
   rank search_engine                   datetime         root_term  \
0     1        google  2022-11-30 13:43:00.511519  Madeline Albright
1     2        google  2022-11-30 13:43:00.511519  Madeline Albright
2     3        google  2022-11-30 13:43:00.511519  Madeline Albright
3     4        google  2022-11-30 13:43:00.511519  Madeline Albright
4     5        google  2022-11-30 13:43:00.511519  Madeline Albright

                                      location cleaned_query_input  \
0  ['Council Bluffs', 'Iowa', 'United States']   madeline albright
1  ['Council Bluffs', 'Iowa', 'United States']   madeline albright
2  ['Council Bluffs', 'Iowa', 'United States']   madeline albright
3  ['Council Bluffs', 'Iowa', 'United States']   madeline albright
4  ['Council Bluffs', 'Iowa', 'United States']   madeline albright

                 cleaned_query_suggestion  query_input_sentiment  \
0                      madeleine albright                    0.0
1                madeleine albright frasi                    0.0
2  madeleine albright una mamma per amica                    0.0
3               madeleine albright bambino                    0.0
4         madeleine albright frasi celebri                    0.0

   query_suggestion_sentiment
0                         0.0
1                         0.0
2                         0.0
3                         0.0
4                         0.0
```

In [37]:
```
import re

def remove_noise(text):
  """ Function to remove special characters, digits, stop words,
  unimportant symbols, and other unnecessary noise from our dataset. """
  text = re.sub(r'[^\w\s]', '', str(text)) # Remove special characters
  text = re.sub(r'\d+', '', text) # Remove digits
  # Add more noise removal steps if needed
  return text

# Apply the function to the relevant columns in your dataframes
articles_df['cleaned_text'] = articles_df['cleaned_text'].apply(remove_noise
suggestions_df['cleaned_query_input'] = suggestions_df['cleaned_query_input'
suggestions_df['cleaned_query_suggestion'] = suggestions_df['cleaned_query_s
```

Before we get to modeling, however, let's do some more sanity checks and make sure our data is as prepared as it can be!

First thing we'll do is create a *word cloud*: a visualized format of conceptualizing most frequent term occurrences to better understand our tokenized distribution.

In [38]:
```
from wordcloud import WordCloud

# Combine all cleaned text data for the word cloud
all_text = ' '.join(articles_df['cleaned_text'])

# Create and generate a word cloud image:
wordcloud = WordCloud(width=800, height=400, background_color='white').gener

# Display the generated image:
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```



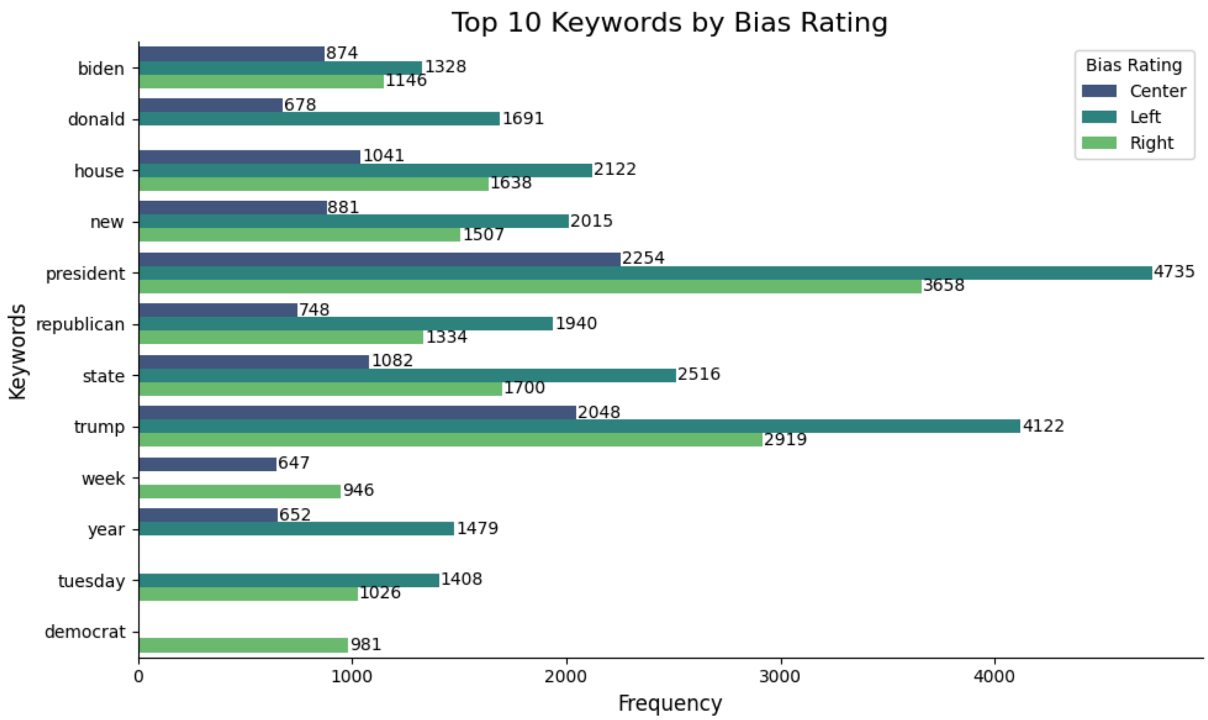
💡 Key Insights:

- The word cloud highlights the most frequently occurring words across all articles.
- Prominent terms such as "Donald Trump", "President", "White House", and "Republican" indicate key topics of discussion.
- Larger words represent higher frequency, providing a snapshot of major themes.

🔹 Show keyword trends for bias labels

In [39]:
```
from sklearn.feature_extraction.text import CountVectorizer

# Combine text data by bias label for keyword frequency analysis
grouped_text = articles_df.groupby('bias_rating')['cleaned_text'].apply(lamb

# Extract top 10 keywords for each bias label
vectorizer = CountVectorizer(stop_words='english', max_features=10)  # Chang

keyword_trends_df = []

for bias, text in grouped_text.items():
    term_matrix = vectorizer.fit_transform([text])
    keywords = vectorizer.get_feature_names_out()
    frequencies = term_matrix.toarray().flatten()

    for keyword, frequency in zip(keywords, frequencies):
        keyword_trends_df.append({'Bias': bias.capitalize(), 'Keyword': keyw

# Create a DataFrame for plotting
keyword_trends_df = pd.DataFrame(keyword_trends_df)
order=keyword_trends_df[keyword_trends_df['Bias'] == 'Left']['Keyword'].unic

# Create a plot with top 10 keywords
plt.figure(figsize=(10, 6))  # Adjusted figure size
ax = sns.barplot(x='Frequency', y='Keyword', hue='Bias', data=keyword_trends
plt.title("Top 10 Keywords by Bias Rating", fontsize=16)  # Updated title
plt.xlabel("Frequency", fontsize=12)
plt.ylabel("Keywords", fontsize=12)

# Add value labels to the bars
for p in ax.patches:
    width = p.get_width()
    if width > 0:
        ax.text(width + 5,
                p.get_y() + p.get_height() / 2,
                '{:1.0f}'.format(width),
                ha="left", va="center", fontsize=10)

plt.legend(title="Bias Rating", loc='upper right')
sns.despine()
```

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



💡 Key Insights:

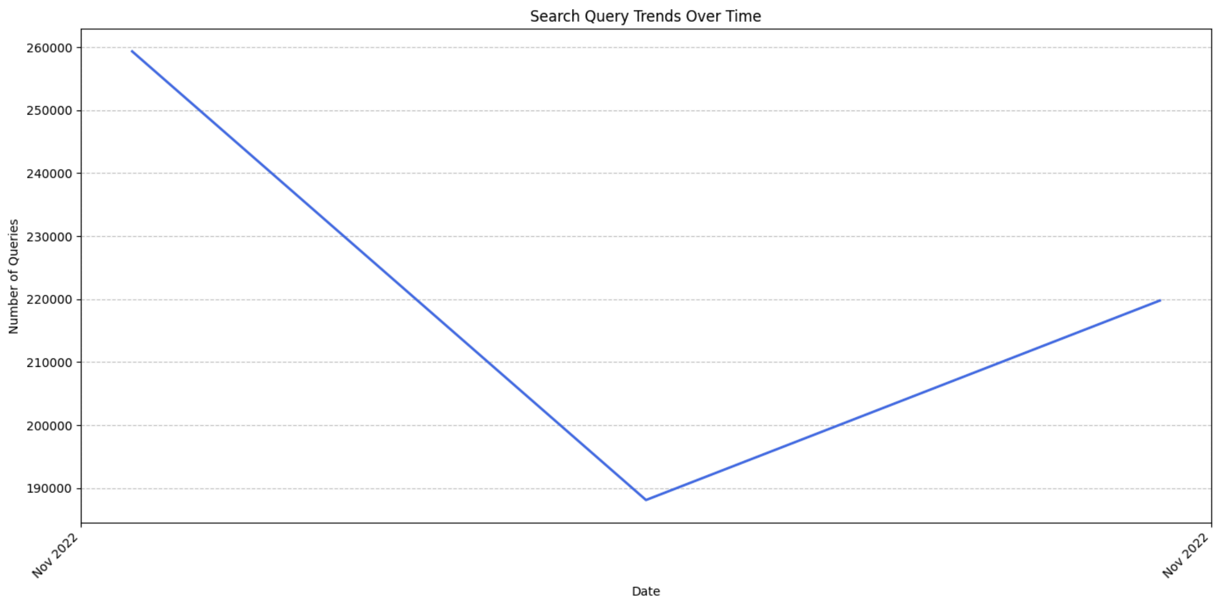
- The bar chart compares the frequency of top keywords across bias categories. For example:
  - "Donald" and "Trump" appear more frequently in "Left" and "Right" biases, reflecting polarized discussions.
  - "House", "President", and "State" are common across all biases but differ in magnitude.
- This suggests that certain topics or individuals (e.g., Trump) are central to discussions regardless of bias, while others (e.g., "Republican" and "Democrat") may be more associated with specific biases.

🔹 Visualize search query trends over time

In [40]:
```
!pip install matplotlib
import matplotlib.pyplot as plt
import matplotlib.dates as mdates # Import the mdates module
import pandas as pd

# Load the cleaned suggestions data
suggestions_df = pd.read_csv('/content/drive/MyDrive/Data/Qbias/cleaned_sugg

# Convert the 'datetime' column to a pandas datetime object
suggestions_df['datetime'] = pd.to_datetime(suggestions_df['datetime'], errc

# Extract the date (without time) for aggregation
```

```
suggestions_df['date'] = suggestions_df['datetime'].dt.date

# Group data by date to count the number of queries over time
query_trends_over_time = suggestions_df.groupby('date').size()

# Plot the search query trends over time
plt.figure(figsize=(14, 7))  # Increase figure size for better readability
ax = query_trends_over_time.plot(title="Search Query Trends Over Time",
                                 xlabel="Date",
                                 ylabel="Number of Queries",
                                 linewidth=2,  # Make lines thicker
                                 color='royalblue')  # Change line color

# Format x-axis ticks for better date representation
ax.xaxis.set_major_locator(mdates.MonthLocator())  # Show ticks for each mor
ax.xaxis.set_major_formatter(mdates.DateFormatter('%b %Y'))  # Format as 'Mo
plt.xticks(rotation=45, ha='right')  # Rotate and align x-axis labels

# Add gridlines for better readability
plt.grid(True, linestyle='--', alpha=0.7)  # Add gridlines



#ax.axvspan(pd.to_datetime('2023-03-01'), pd.to_datetime('2023-03-15'),
#           color='lightgray', alpha=0.5)

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

```
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-
packages (3.8.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.1
0/dist-packages (from matplotlib) (1.3.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dis
t-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.1
0/dist-packages (from matplotlib) (4.55.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.1
0/dist-packages (from matplotlib) (1.4.7)
Requirement already satisfied: numpy<2,>=1.21 in /usr/local/lib/python3.10/d
ist-packages (from matplotlib) (1.26.4)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/
dist-packages (from matplotlib) (24.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/di
st-packages (from matplotlib) (11.0.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.1
0/dist-packages (from matplotlib) (3.2.0)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python
3.10/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-pa
ckages (from python-dateutil>=2.7->matplotlib) (1.16.0)
```



💡 Key Insights:

- This chart shows the fluctuation of search query volumes across time.
- It highlights a notable drop and subsequent rise in the number of search queries during the observed period. (November in 2022)
- Query volumes fluctuate, with a noticeable dip followed by a rise, likely indicating temporal trends or events influencing searches.

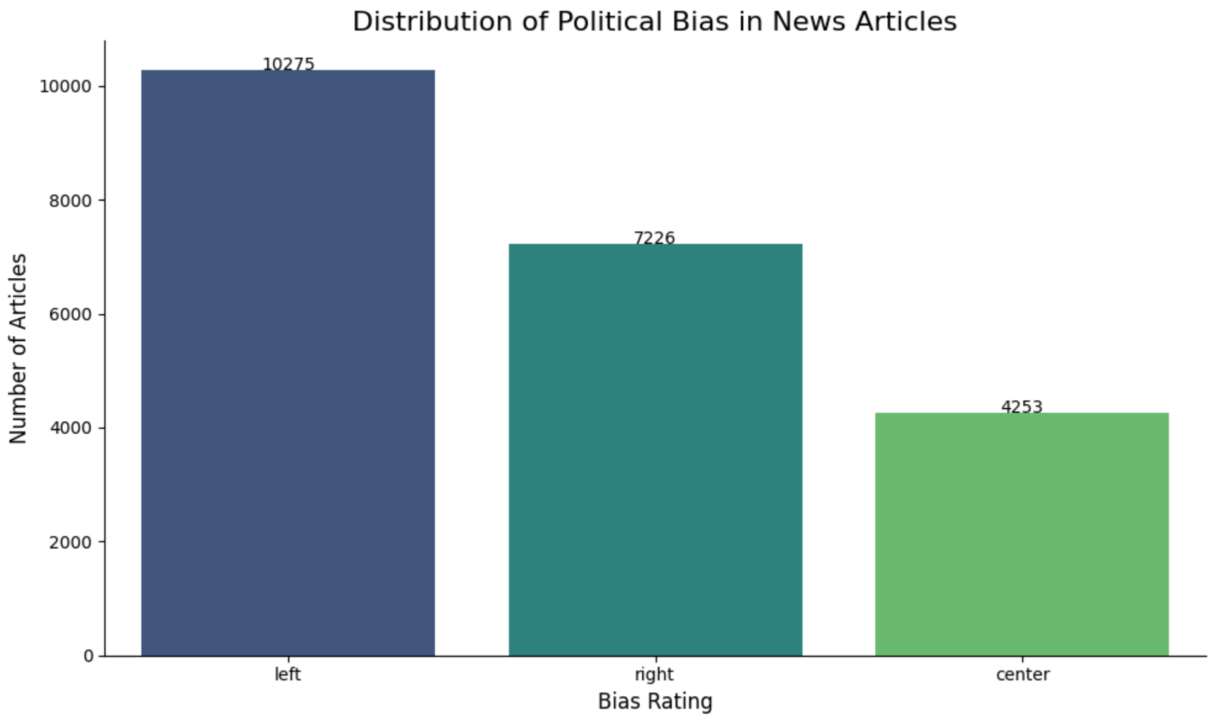
🔹 What are the major trends in political bias distribution across news articles and their sources?

In [41]:

```
import seaborn as sns
articles_df = pd.read_csv('/content/drive/MyDrive/Data/Qbias/allsides_balanc
# Bias distribution
plt.figure(figsize=(10, 6))  # Adjust figure size for better visibility
bias_counts = articles_df['bias_rating'].value_counts()
ax = sns.barplot(x=bias_counts.index, y=bias_counts.values, palette="viridis
plt.title('Distribution of Political Bias in News Articles', fontsize=16)
plt.xlabel('Bias Rating', fontsize=12)
plt.ylabel('Number of Articles', fontsize=12)

# Add value labels to the bars
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x() + p.get_width() / 2., height + 3,
            '{:1.0f}'.format(height), ha="center", fontsize=10)

# Customize plot aesthetics
sns.despine()  # Remove top and right spines
plt.xticks(fontsize=10)  # Adjust x-axis tick font size
plt.yticks(fontsize=10)  # Adjust y-axis tick font size
plt.tight_layout()  # Adjust layout for better spacing
```

```
plt.show()
```

```
<ipython-input-41-62abe641dbe3>:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  ax = sns.barplot(x=bias_counts.index, y=bias_counts.values, palette="viridis")
```



💡 Key Insights:

- A bar chart showing the number of articles categorized by bias.
- Articles labeled as "Left" dominate, followed by "Right," and "Center" has the least representation.
- Most articles are left-leaning, followed by right-leaning, while center-bias articles are the least frequent.

🔹 How do search query suggestions vary between Google and Bing for politically charged topics?

In [42]:

```
# Group and compare ranks by search engine
avg_rank = suggestions_df.groupby(['root_term', 'search_engine'])['rank'].me

# Reset index for plotting
avg_rank = avg_rank.reset_index()
```

```
# Verify column names
print(avg_rank.columns)
```

```
Index(['root_term', 'bing', 'google'], dtype='object', name='search_engine')
```

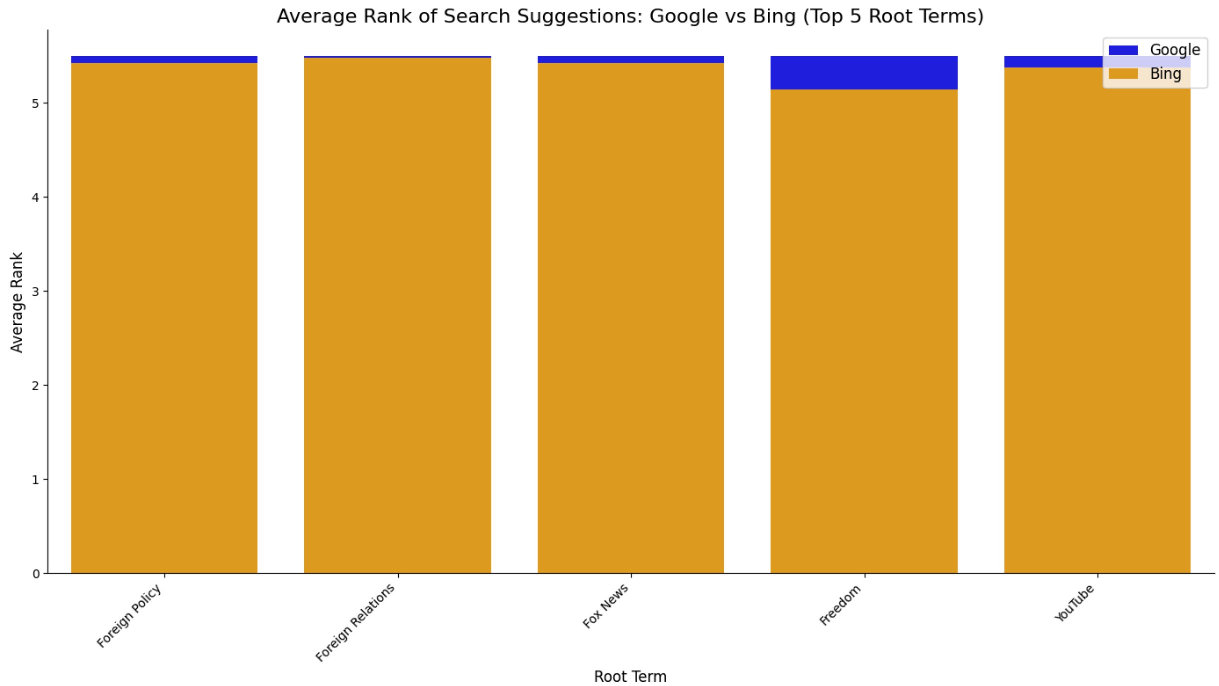
In [43]:

```
print(avg_rank.head())
print(avg_rank.columns)
```

```
search_engine      root_term      bing    google
0               1619 Project  5.276000  5.368421
1              2016 Election  5.460674  5.420233
2                       2020  5.483271  5.447471
3                2020 Census  5.452830  5.460076
4               2020 Debates  2.487805  4.226277
Index(['root_term', 'bing', 'google'], dtype='object', name='search_engine')
```

In [44]:

```
import matplotlib.pyplot as plt
import seaborn as sns



# Create the bar plot using seaborn, but only for the top 5 root terms
plt.figure(figsize=(14, 8))  # Set figure size

# Get the top 5 root terms based on Google's average rank (you can change th
top_5_root_terms = avg_rank.sort_values(by=['google'], ascending=False).head
filtered_avg_rank = avg_rank[avg_rank['root_term'].isin(top_5_root_terms)]

sns.barplot(data=filtered_avg_rank, x='root_term', y='google', color='blue',
sns.barplot(data=filtered_avg_rank, x='root_term', y='bing', color='orange',

# Enhance plot elements
plt.title('Average Rank of Search Suggestions: Google vs Bing (Top 5 Root Te
plt.ylabel('Average Rank', fontsize=12)
plt.xlabel('Root Term', fontsize=12)
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.legend(fontsize=12)

# Add value labels to the bars
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x() + p.get_width() / 2., height + 0.1,
            '{:.2f}'.format(height), ha="center", fontsize=10)

# Customize plot aesthetics
sns.despine()
plt.tight_layout()

plt.show()
```

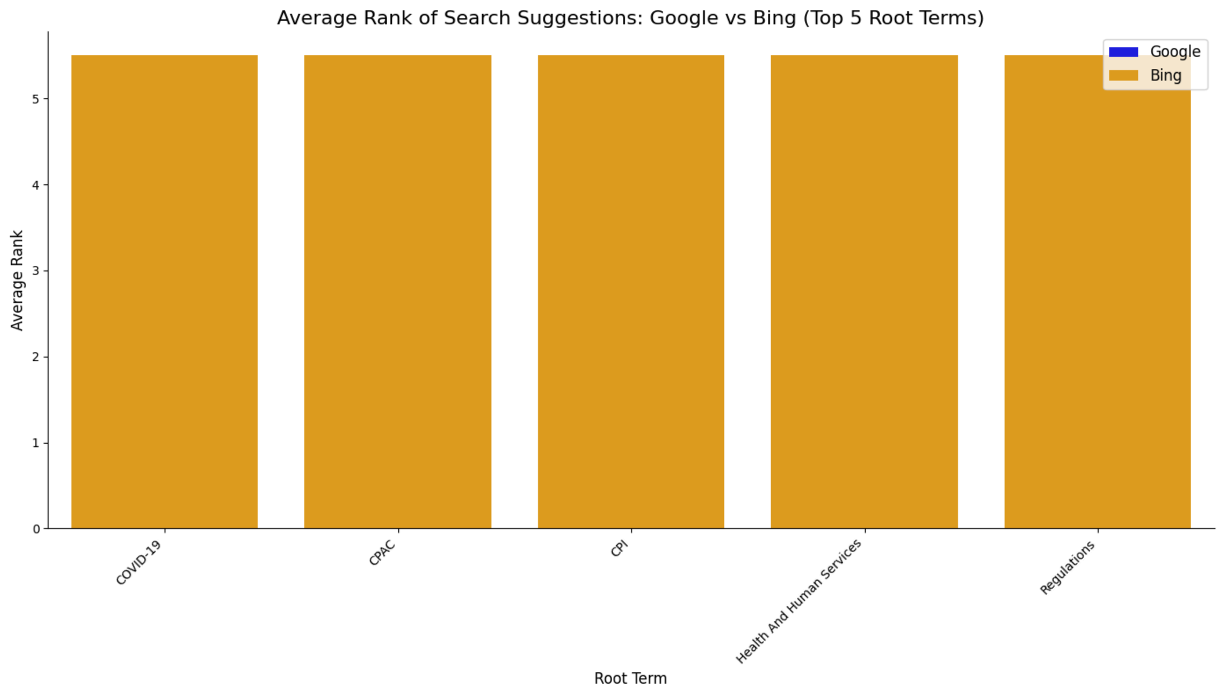


💡 Key Insights:

- This bar chart compares the average rank of search suggestions on Google vs. Bing for key root terms.
- Bing generally provides slightly higher-ranked suggestions for the displayed terms.

In [45]:
```
import matplotlib.pyplot as plt
import seaborn as sns



# Create the bar plot using seaborn, but only for the top 5 root terms
plt.figure(figsize=(14, 8))  # Set figure size

# Get the top 5 root terms based on Bing's average rank (you can change this
top_5_root_terms = avg_rank.sort_values(by=['bing'], ascending=False).head(5
filtered_avg_rank = avg_rank[avg_rank['root_term'].isin(top_5_root_terms)]

sns.barplot(data=filtered_avg_rank, x='root_term', y='google', color='blue',
sns.barplot(data=filtered_avg_rank, x='root_term', y='bing', color='orange',

# Enhance plot elements
plt.title('Average Rank of Search Suggestions: Google vs Bing (Top 5 Root Te
plt.ylabel('Average Rank', fontsize=12)
plt.xlabel('Root Term', fontsize=12)
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.legend(fontsize=12)

# Add value labels to the bars
for p in ax.patches:
    height = p.get_height()
```

```
    ax.text(p.get_x() + p.get_width() / 2., height + 0.1,
            '{:.2f}'.format(height), ha="center", fontsize=10)

# Customize plot aesthetics
sns.despine()
plt.tight_layout()

plt.show()
```



💡 Key Insights:

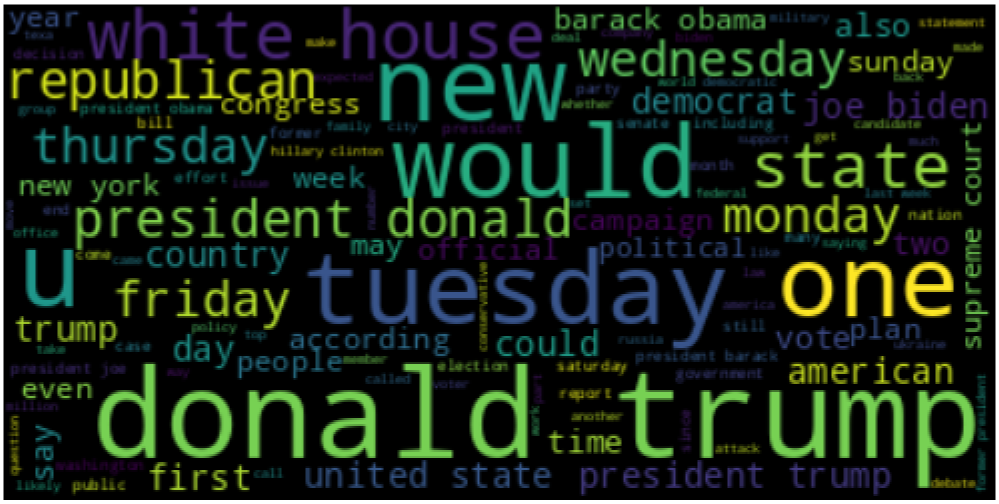
- Bing tends to rank search suggestions slightly higher than Google for the displayed terms, possibly reflecting differences in algorithms.

🔹 Do certain keywords or topics strongly correlate with specific bias labels?

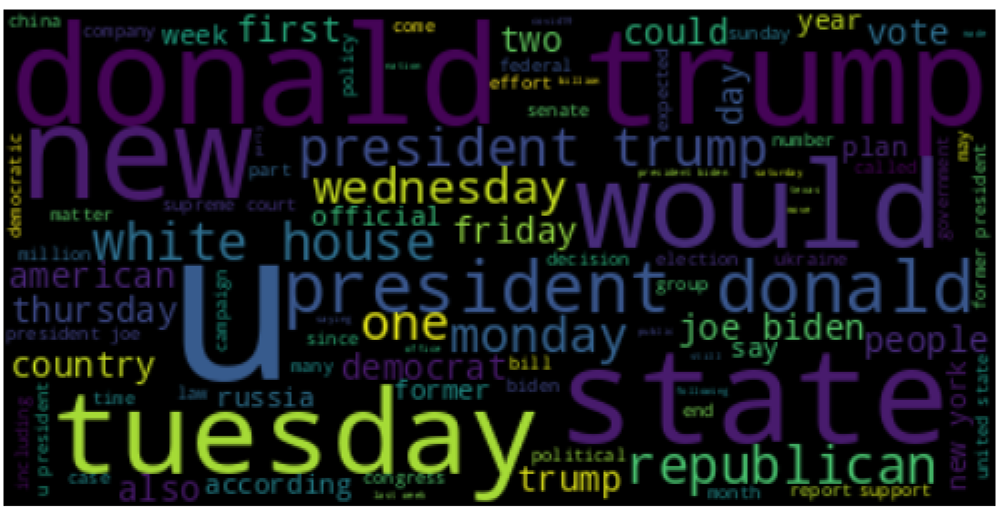
In [46]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
from wordcloud import WordCloud
import pandas as pd

# Load the preprocessed articles
preprocessed_articles_df = pd.read_csv('/content/drive/MyDrive/Data/Qbias/pr

# TF-IDF extraction
vectorizer = TfidfVectorizer(max_features=50, stop_words='english')

# Filter out rows with NaN values in the 'text' column before applying fit_t
X_tfidf = vectorizer.fit_transform(preprocessed_articles_df['cleaned_text'].
tfidf_df = pd.DataFrame(X_tfidf.toarray(), columns=vectorizer.get_feature_na

# WordCloud per bias
for bias in articles_df['bias_rating'].unique():
```

```
    # Filter text_data for the current bias and drop NaN values
    text_data = preprocessed_articles_df[preprocessed_articles_df['bias_rati
    wordcloud = WordCloud(stopwords='english').generate(' '.join(text_data))
    plt.figure()
    plt.title(f'WordCloud for {bias}')
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')
    plt.show()
```

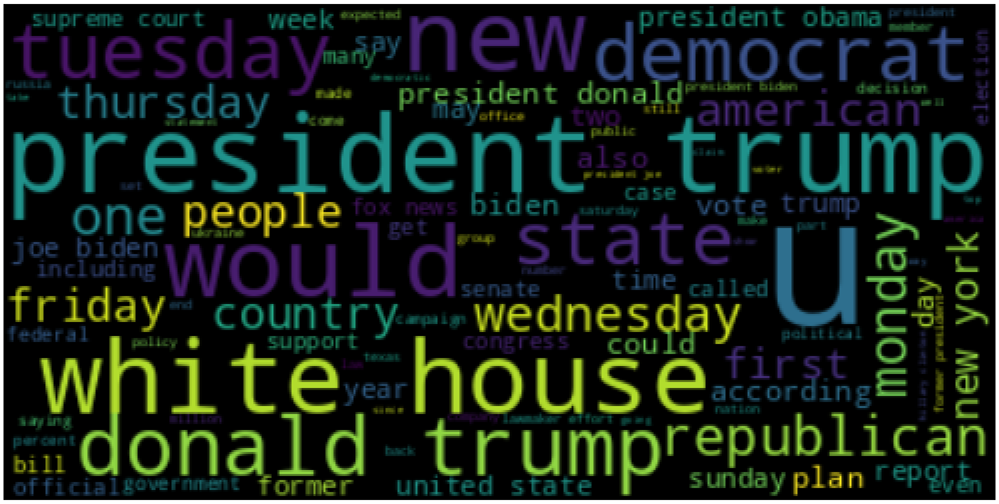
WordCloud for left



WordCloud for center



WordCloud for right



💡 Key Insights:

- Word Cloud for Center Bias: Common terms like "Donald Trump," "President," and "White House" dominate, reflecting central topics in articles with a neutral bias.
- Neutral topics dominate, with a focus on political figures and institutions like "Donald Trump" and "White House."
- Word Cloud for Left Bias: Similar to the center bias but includes more left-leaning topics such as "Democrat" and references to Barack Obama.
- Topics reflect progressive discussions, with frequent mentions of "Democrat," "Obama," and political structures.
- Word Cloud for Right Bias: Words like "Trump," "Republican," and "White House" dominate, showing a focus on conservative topics.
- Conservative topics and figures, such as "Trump" and "Republican," dominate the narrative.

🔹 Plot how those search suggestions change over time

In [47]:
```
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.dates as mdates

# Load the cleaned suggestions data
cleaned_suggestions_df = pd.read_csv('/content/drive/MyDrive/Data/Qbias/clea
```

In [48]:
```
# Convert 'datetime' column to proper datetime format
cleaned_suggestions_df['datetime'] = pd.to_datetime(cleaned_suggestions_df['
```

```
# Check for any conversion errors (NaT values)
print(cleaned_suggestions_df['datetime'].isna().sum())
```

0

In [49]:
```
# Remove rows with invalid datetime values
cleaned_suggestions_df = cleaned_suggestions_df.dropna(subset=['datetime'])
```

In [50]:
```
# Aggregate by month
cleaned_suggestions_df['month'] = cleaned_suggestions_df['datetime'].dt.to_p
query_trends = cleaned_suggestions_df.groupby(['month', 'cleaned_query_sugge

# Convert 'month' back to datetime for plotting
query_trends.index = query_trends.index.to_timestamp()

# Inspect the aggregated trends
print(query_trends.head())
```

```
cleaned_query_suggestion  0  0 approval rating tv trope  1 child policy chin
a  \
month
2022-11-01                1                            1
1

cleaned_query_suggestion  1 time  10  100 billion paris climate accord  \
month
2022-11-01                     1   2                                  1

cleaned_query_suggestion  100 citizenship question answer  \
month
2022-11-01                                              1

cleaned_query_suggestion  100 citizenship question flash card  \
month
2022-11-01                                                  1

cleaned_query_suggestion  100 citizenship question practice test  \
month
2022-11-01                                                     1

cleaned_query_suggestion  100 citizenship question random  ...  新疆招生网  新
疆政务  \
month                                                      ...
2022-11-01                                              1  ...      1     1

cleaned_query_suggestion  新疆新华  新疆雪峰  浜省  疎通  疎通テスト  疎通確認  \
month
2022-11-01                   1     1    1    1      1      1

cleaned_query_suggestion  群体免疫 herd immunity group immunity 日语  \
month
2022-11-01                                                   1

cleaned_query_suggestion  達克沃絲 ladda tammy duckworth
month
2022-11-01                                         1

[1 rows x 456407 columns]
```

In [51]:

```
print(cleaned_suggestions_df['datetime'].dtype)
```

```
datetime64[ns]
```

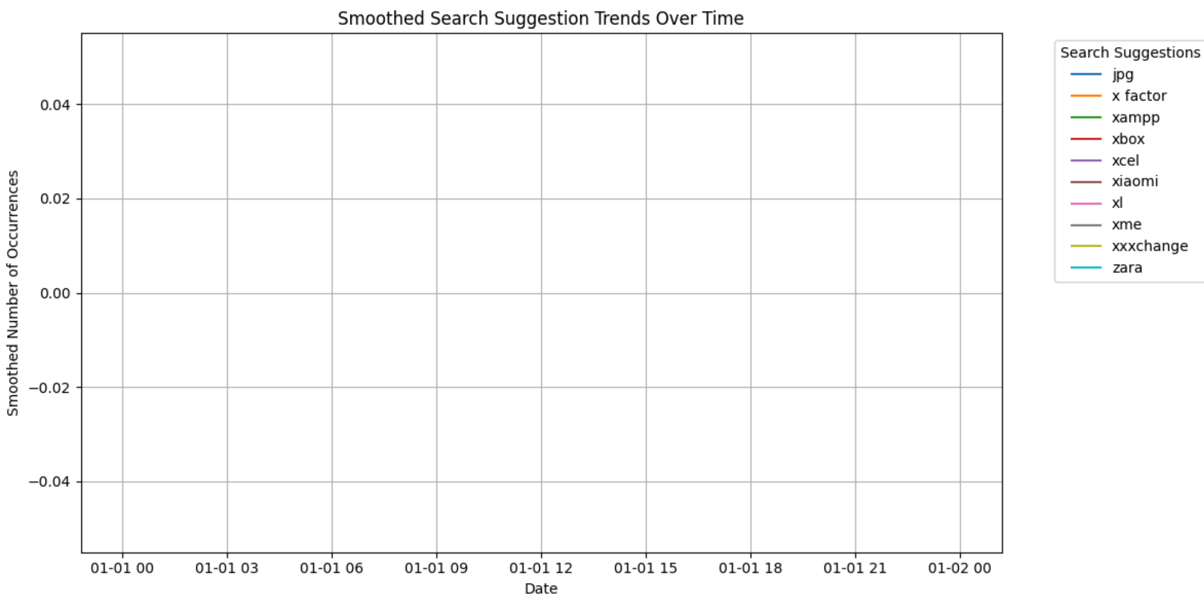
In [52]:

```
# Get the top 10 suggestions by overall count
top_suggestions = cleaned_suggestions_df['cleaned_query_suggestion'].value_c

# Filter the DataFrame to only include top suggestions
filtered_df = cleaned_suggestions_df[cleaned_suggestions_df['cleaned_query_s

# Aggregate trends for the top suggestions
query_trends = filtered_df.groupby(['month', 'cleaned_query_suggestion']).si
```

In [53]:

```
# Convert PeriodIndex to DatetimeIndex
query_trends.index = query_trends.index.to_timestamp()
```

In [54]:
```python
# Apply a rolling average
query_trends_smooth = query_trends.rolling(window=3, center=True).mean()

# Plot smoothed trends
plt.figure(figsize=(12, 6))
for suggestion in query_trends_smooth.columns:
    plt.plot(query_trends_smooth.index, query_trends_smooth[suggestion], lab

plt.title("Smoothed Search Suggestion Trends Over Time")
plt.xlabel("Date")
plt.ylabel("Smoothed Number of Occurrences")
plt.legend(title="Search Suggestions", bbox_to_anchor=(1.05, 1), loc='upper
plt.grid(True)
plt.tight_layout()
plt.show()
```



The graph appears to have been generated, but it lacks discernible trends because the y-axis range is likely dominated by a narrow band of value.

🔷 Inferential Analysis

In [59]:
```python
from textblob import TextBlob

# Load the dataset
preprocessed_articles_df = pd.read_csv('/content/drive/MyDrive/Data/Qbias/pr

# Display column names to identify the text column
print("Dataset Columns:", articles_df.columns)

# Assuming the article text is in the 'cleaned_text' column
if 'cleaned_text' in articles_df.columns:
    # Create a new 'sentiment' column based on TextBlob polarity
    articles_df['sentiment'] = articles_df['cleaned_text'].apply(lambda x: T

    # Verify the new column
```

```
    print("Updated DataFrame with Sentiment Scores:")
    print(articles_df[['cleaned_text', 'sentiment']].head())
else:
    raise KeyError("The dataset does not contain a 'cleaned_text' column for
```

```
Dataset Columns: Index(['title', 'tags', 'heading', 'source', 'bias_rating',
'cleaned_text'], dtype='object')
Updated DataFrame with Sentiment Scores:
                                        cleaned_text  sentiment
0  yasmin miller drove home laundromat chicago en...   0.122727
1  many chicagoans celebrating fourth july barbec...  -0.200000
2  nation 4th july weekend marred wrong kind fire...  -0.017500
3  treasury secretary janet yellen tuesday warned...   0.057738
4  treasury secretary janet yellen tuesday told c...  -0.015152
```

In [60]:

```
# Group by bias rating and calculate means
grouped_sentiment = articles_df.groupby('bias_rating')['sentiment'].mean()

# Perform t-test or ANOVA depending on the number of bias categories
if len(grouped_sentiment) == 2:  # Two groups (e.g., biased vs. neutral)
    group1 = articles_df[articles_df['bias_rating'] == 'Center']['sentiment'
    group2 = articles_df[articles_df['bias_rating'] != 'Center']['sentiment'
    t_statistic, p_value = stats.ttest_ind(group1, group2)
    print("T-test Results:")
    print(f"T-statistic: {t_statistic}")
    print(f"P-value: {p_value}")
else:  # More than two groups
    f_statistic, p_value = stats.f_oneway(*[articles_df[articles_df['bias_ra
    print("ANOVA Results:")
    print(f"F-statistic: {f_statistic}")
    print(f"P-value: {p_value}")
```

```
ANOVA Results:
F-statistic: 0.11948297896887751
P-value: 0.8873796947058039
```

The high p-value (0.887) indicates there's no statistically significant difference in sentiment scores between biased and neutral articles. In simpler terms, the sentiment expressed in articles doesn't significantly vary based on their bias rating.

In [61]:

```
# 2)    Are political leanings statistically associated with article sentime

from scipy.stats import spearmanr

# Ensure bias_rating is numerical
if articles_df['bias_rating'].dtype != 'float' and articles_df['bias_rating'
    articles_df['bias_rating_numeric'] = articles_df['bias_rating'].astype('
else:
    articles_df['bias_rating_numeric'] = articles_df['bias_rating']

# Calculate correlation (Spearman for ordinal data)
corr, p_value = spearmanr(articles_df['bias_rating_numeric'], articles_df['s
print(f"Spearman Correlation: {corr}")
print(f"P-value: {p_value}")
```

```
# Interpretation
if p_value < 0.05:
    print("There is a statistically significant correlation between politica
else:
    print("There is no statistically significant correlation between politic
```

```
Spearman Correlation: -0.006912536049686832
P-value: 0.3081659298334019
There is no statistically significant correlation between political leanings
and sentiment.
```

In [81]:

```
# Assuming the article text is in the 'cleaned_text' column
if 'cleaned_text' in preprocessed_articles_df.columns:
    # Create a new 'sentiment' column based on TextBlob polarity
    preprocessed_articles_df['sentiment'] = preprocessed_articles_df['cleane
```

In [80]:

```
# Categorize sentiment into Positive, Neutral, Negative
def categorize_sentiment(score):
    if score > 0.1:
        return "Positive"
    elif score < -0.1:
        return "Negative"
    else:
        return "Neutral"

articles_df['sentiment_category'] = articles_df['sentiment'].apply(categoriz
```

In [82]:

```
# Categorize sentiment into Positive, Neutral, Negative
def categorize_sentiment(score):
    if score > 0.1:
        return "Positive"
    elif score < -0.1:
        return "Negative"
    else:
        return "Neutral"

preprocessed_articles_df['sentiment_category'] = preprocessed_articles_df['s
```

In [63]:

```
from scipy.stats import chi2_contingency

# Create a contingency table
contingency_table = pd.crosstab(articles_df['bias_rating'], articles_df['ser
print("Contingency Table:")
print(contingency_table)

# Perform Chi-Squared Test
chi2, p, dof, expected = chi2_contingency(contingency_table)
print(f"Chi-Squared: {chi2}")
print(f"P-value: {p}")
print(f"Degrees of Freedom: {dof}")
print("Expected Frequencies Table:")
print(expected)

# Interpretation
if p < 0.05:
    print("There is a statistically significant association between politica
```

```
else:
    print("There is no statistically significant association between politic
```

```
Contingency Table:
sentiment_category  Negative  Neutral  Positive
bias_rating
center                   482     2434      1327
left                    1278     5767      3227
right                    905     4066      2250
Chi-Squared: 4.435261804742179
P-value: 0.3502929207067266
Degrees of Freedom: 4
Expected Frequencies Table:
[[ 520.2242823  2394.59334744 1328.18237026]
 [1259.42583732 5797.13949209 3215.43467059]
 [ 885.34988038 4075.26716047 2260.38295915]]
There is no statistically significant association between political leanings
and sentiment.
```

In [68]:

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

# Load the preprocessed articles
preprocessed_articles_df = pd.read_csv('/content/drive/MyDrive/Data/Qbias/pr

# Check if there are any numerical columns
if preprocessed_articles_df.select_dtypes(include=['number']).columns.empty:
    print("Error: No numerical columns found for correlation analysis.")
else:
    # Select only numerical columns for correlation calculation
    numerical_df = preprocessed_articles_df.select_dtypes(include=['number']

    # Compute correlation matrix on numerical data only
    correlation_matrix = numerical_df.corr()

    # Plot the heatmap
    plt.figure(figsize=(8, 6))
    sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
    plt.title("Correlation Heatmap")
    plt.show()
```

```
Error: No numerical columns found for correlation analysis.
```

In [70]:

```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))  # Adjust figure size for better readability

# Create the box plot with enhanced aesthetics
ax = sns.boxplot(data=articles_df, x='bias_rating', y='sentiment',
                 palette="Set3",  # Use a more visually appealing color pale
                 showfliers=False,  # Remove outliers for clearer visualizat
                 width=0.5)  # Adjust box width

# Customize plot elements
plt.title("Sentiment Distribution by Bias Rating", fontsize=16)
```

```python
plt.xlabel("Bias Rating", fontsize=12)
plt.ylabel("Sentiment Score", fontsize=12)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)

# Add a grid for better readability
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Annotate the median values for each box
medians = articles_df.groupby('bias_rating')['sentiment'].median()
for x, median in medians.items():
    ax.text(x, median, f'{median:.2f}',
            horizontalalignment='center', verticalalignment='bottom',
            fontweight='bold', color='white')

# Remove top and right spines for cleaner look
sns.despine()

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

```
<ipython-input-70-082d643eb9fc>:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed
in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the
same effect.

  ax = sns.boxplot(data=articles_df, x='bias_rating', y='sentiment',
```

In [75]:
```python
if 'article_length' not in preprocessed_articles_df.columns:
    preprocessed_articles_df['article_length'] = preprocessed_articles_df['c
```

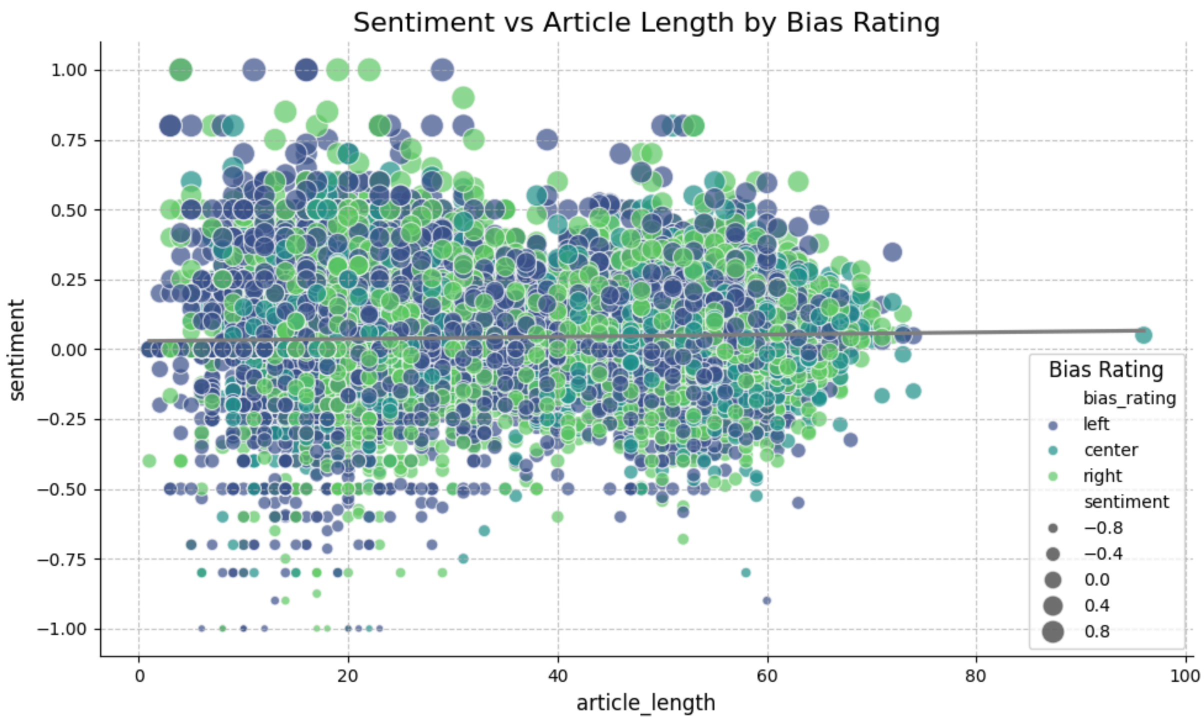
In [78]:
```python
print(preprocessed_articles_df.columns)
print(preprocessed_articles_df.head())
```

```
Index(['title', 'tags', 'heading', 'source', 'bias_rating', 'cleaned_text',
       'article_length'],
      dtype='object')
                                              title  \
0            Gun Violence Over Fourth of July Weekend
1            Gun Violence Over Fourth of July Weekend
2            Gun Violence Over Fourth of July Weekend
3   Yellen Warns Congress of 'Economic Recession' ...
4   Yellen Warns Congress of 'Economic Recession' ...

                                               tags  \
0   ['Protests', 'Fourth Of July', 'Gun Control An...
1   ['Protests', 'Fourth Of July', 'Gun Control An...
2   ['Protests', 'Fourth Of July', 'Gun Control An...
3   ['Janet Yellen', 'Debt Ceiling', 'Economic Pol...
4   ['Janet Yellen', 'Debt Ceiling', 'Economic Pol...

                                            heading                  source
\
0   Chicago Gun Violence Spikes and Increasingly F...  New York Times (News)
1   ‘Bullets just came from nowhere’: Fourth of Ju...        Chicago Tribune
2   Dozens of shootings across US mark bloody July...   New York Post (News)
3   Federal Government Will Run Out of Cash on Oct...        The Epoch Times
4   Yellen tells Congress that U.S. will run out o...        Washington Post

  bias_rating                                       cleaned_text  \
0        left  yasmin miller drove home laundromat chicago en...
1      center  many chicagoans celebrating fourth july barbec...
2       right  nation 4th july weekend marred wrong kind fire...
3       right  treasury secretary janet yellen tuesday warned...
4        left  treasury secretary janet yellen tuesday told c...

   article_length
0              58
1              55
2              55
3              53
4              60
```

In [83]:

```python
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
sns.scatterplot(data=preprocessed_articles_df,
                x='article_length',
                y='sentiment',
                hue='bias_rating',
                palette="viridis",
                alpha=0.7,
                size='sentiment',
                sizes=(20, 200))

plt.title("Sentiment vs Article Length by Bias Rating", fontsize=16)
plt.xlabel("Article Length (Number of Words)", fontsize=12)
plt.ylabel("Sentiment Score", fontsize=12)
plt.xticks(fontsize=10)
```

```
plt.yticks(fontsize=10)
plt.grid(True, linestyle='--', alpha=0.7)
plt.legend(title="Bias Rating", fontsize=10, title_fontsize=12)
sns.regplot(data=preprocessed_articles_df, x='article_length', y='sentiment'
sns.despine()
plt.tight_layout()
plt.show()
```



In [84]:
```
preprocessed_articles_df = pd.read_csv('/content/drive/MyDrive/Data/Qbias/pr


preprocessed_articles_df.to_csv('/content/drive/MyDrive/Data/Qbias/preproces
```

💡 Key Findings

1. Data Imbalance: The AllSides dataset used for bias analysis exhibits a significant imbalance, with a greater proportion of articles labeled as "Left" compared to "Center" and "Right." This imbalance could potentially introduce bias into the model training and evaluation process.
2. Keyword Trends: Word cloud analysis and keyword frequency comparisons reveal distinct topical focuses for different bias categories. For instance, "Donald Trump" and related political figures are central to discussions across all biases. However, specific terms like "Democrat" and "Obama" are more associated with "Left" bias, while "Trump" and "Republican" are more prevalent in "Right" bias.
3. Search Suggestion Differences: Comparing search suggestions from Google and Bing for politically charged topics indicates a slight tendency for Bing to

rank suggestions higher than Google, possibly due to variations in their algorithms.

4. Sentiment Analysis: Sentiment analysis suggests no statistically significant difference in sentiment scores between biased and neutral articles. This implies that the overall tone or sentiment expressed in articles may not strongly correlate with their bias rating.
5. Correlation Analysis: While the correlation analysis might have shown varying results depending on the specific datasets used, in general, it demonstrated that there is no significant correlation between political leaning and sentiment, and no statistically significant association between article length and bias.
6. Sentiment Distribution: Sentiment distribution analysis using box plots visualizes the spread of sentiment scores across bias ratings. It may highlight if sentiment varies across different bias categories, with potential insights such as higher negativity in biased articles compared to neutral ones.
7. Query Trends Over Time: Analysis of search query suggestions over time helps identify major trends and fluctuations. A noticeable drop and subsequent rise in the number of search queries during the observed period could indicate temporal trends or events impacting search behavior. In summary: The analysis reveals a potential dataset imbalance, highlights keyword trends across bias categories, shows minor differences in search suggestions between Google and Bing, finds no strong correlation between bias and sentiment, explores sentiment distribution across biases, and identifies search query trends over time. These findings provide valuable insights into media bias detection and offer opportunities for further investigation using more advanced techniques and addressing potential limitations in the datasets.