part1

1. I will use regex to keep letters, numbers, and special characters that may meaningful, such as '&', '-', '%', '?', '!', remove words "yeah". I will use cross-validation to better reflect the stability of the model.

In [1]:

```
import pandas as pd
import nltk
import regex as re
from nltk.corpus import stopwords, wordnet
from nltk.tokenize import word_tokenize
from nltk import pos_tag
from nltk.stem import WordNetLemmatizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import cross_validate
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_sc
import matplotlib.pyplot as plt
from sklearn.pipeline import Pipeline
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np
from sklearn.preprocessing import normalize
import random
from sklearn.metrics.pairwise import cosine_similarity, euclidean_distances, lin
```

In [2]:

```
# Load dataset
df = pd.read_csv("dataset.tsv", sep="\t")

print(df.head())
```

```
                        artist_name           track_name  release_date  \
0                            loving  the not real lake          2016
1                           incubus     into the summer          2019
2                         reignwolf            hardcore          2016
3                 tedeschi trucks band           anyhow          2016
4  lukas nelson and promise of the real  if i started over          2017

   genre                                             lyrics      topic
0   rock  awake know go see time clear world mirror worl...       dark
1   rock  shouldn summer pretty build spill ready overfl...  lifestyle
2  blues  lose deep catch breath think say try break wal...    sadness
3  blues  run bitter taste take rest feel anchor soul pl...    sadness
4  blues  think think different set apart sober mind sym...       dark
```

In [3]:

```
# concatenate all the informations for one song in df['all_text']
df['artist_name'] = df['artist_name'].fillna('').str.lower()
df['track_name'] = df['track_name'].fillna('').str.lower()
df['release_date'] = pd.to_datetime(df['release_date'], errors='coerce').dt.year
df['genre'] = df['genre'].fillna('').str.lower()
df['lyrics'] = df['lyrics'].fillna('').str.lower()
df['all_text'] = df['artist_name'] +  ' ' + df['track_name'] + ' '  + df['releas
print(df['all_text'])
```

```
0       loving the not real lake 1970 rock awake know ...
1       incubus into the summer 1970 rock shouldn summ...
2       reignwolf hardcore 1970 blues lose deep catch ...
3       tedeschi trucks band anyhow 1970 blues run bit...
4       lukas nelson and promise of the real if i star...
                                ...
1495    ra ra riot absolutely 1970 rock year absolutel...
1496    mat kearney face to face 1970 rock breakthroug...
1497    owane born in space 1970 jazz look look right ...
1498    nappy roots blowin' trees 1970 hip hop nappy r...
1499    skillet stars 1970 rock speak word life begin ...
Name: all_text, Length: 1500, dtype: object
```

2. **Preprocessing**

Lowercasing: set lower case for all the words.

Regex: use regex libaray rather than re to keep words in other language.

Stopwords: using stopwords from NLTK libaray and keep the meaningful words like 'not', 'but'.

Word tokenize: use word_tokenize to split the text to words.

Lemmatization: Lemmatization processes words more accurately. It is beneficial for the subsequent sentiment analysis.

In [94]:
```python
# Download required NLTK data
nltk.download('punkt_tab')
nltk.download('wordnet')
nltk.download('stopwords')
nltk.download('averaged_perceptron_tagger_eng')
# Init tools
lemmatizer = WordNetLemmatizer()
stop_words = set(stopwords.words('english')) - {'not', 'no', 'but', 'very'}

# POS mapping function
def get_wordnet_pos(tag):
    if tag.startswith('J'):
        return wordnet.ADJ
    elif tag.startswith('V'):
        return wordnet.VERB
    elif tag.startswith('N'):
        return wordnet.NOUN
    elif tag.startswith('R'):
        return wordnet.ADV
    else:
        return wordnet.NOUN

# Preprocessing function
def preprocess_text(text):
    text = text.lower()


    # Keep letters, numbers, select punctuation
    text = re.sub(r"[^\p{L}\p{N}\s/'\-!?&$#%@*]", ' ', text)
```

```
    # remove connecting words in lyrics: yeah
    text = re.sub(r'\byeah\b', '', text)


    # Tokenize into words
    tokens = word_tokenize(text)

    # Remove stopwords
    tokens = [word for word in tokens if word not in stop_words]

    # Lemmatization
    pos_tags = pos_tag(tokens)

    # Lemmatize with correct POS
    lemmatized = [lemmatizer.lemmatize(word, get_wordnet_pos(pos)) for word, pos

    return ' '.join(lemmatized)
```

```
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger_eng to
[nltk_data]     /root/nltk_data...
[nltk_data]   Package averaged_perceptron_tagger_eng is already up-to-
[nltk_data]       date!
```

In [54]:
```
# apply preprocessing
df['clean'] = df['all_text'].apply(preprocess_text)
print(df['clean'].head())
```

```
0    love not real lake 1970 rock awake know go see...
1    incubus summer 1970 rock summer pretty build s...
2    reignwolf hardcore 1970 blue lose deep catch b...
3    tedeschi truck band anyhow 1970 blue run bitte...
4    lukas nelson promise real started 1970 blue th...
Name: clean, dtype: object
```

In [55]:
```
X_text = df['clean']
y = df['topic']

# use countVectorizer
count_vec = CountVectorizer()
X = count_vec.fit_transform(X_text)

# check if dataset balanced
print(df['topic'].value_counts(normalize=True))
```

```
topic
dark         0.326667
sadness      0.250667
personal     0.231333
lifestyle    0.136667
emotion      0.054667
Name: proportion, dtype: float64
```

3. **metrics**

Accuracy: The proportion of correctly predicted samples to the total samples, suitable for balanced dataset.

Balanced Accuracy: Average of the recall obtained on each class, suitable for unbalanced dataset.

Micro-F1: F1 value calculated after global statistics TP/FP/FN, is significantly affected by large categories.

Macro-F1: unweighted mean of the F1 scores calculated in each class. It treats all class equally.

Macro precision: the average of the precision values for each class. Useful for unbalanced dataset.

Macro recall: the average of the recall values computed independently for each class, it treats all the class equally.

Since this dataset is unbalanced, I will use the metrics Macro-F1, Macro precision, and Macro recall.

According to the bar chart below, we can notice that MNB performs better than BNB.

In [56]:
```
# metrics selected
scoring = {

    'macro_precision': 'precision_macro',
    'macro_recall': 'recall_macro',
    'macro_f1': 'f1_macro'
}

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

bnb = BernoulliNB()
mnb = MultinomialNB()

# use cross validation to get score
bnb_scores = cross_validate(bnb, X, y, cv=cv, scoring=scoring)
mnb_scores = cross_validate(mnb, X, y, cv=cv, scoring=scoring)
```

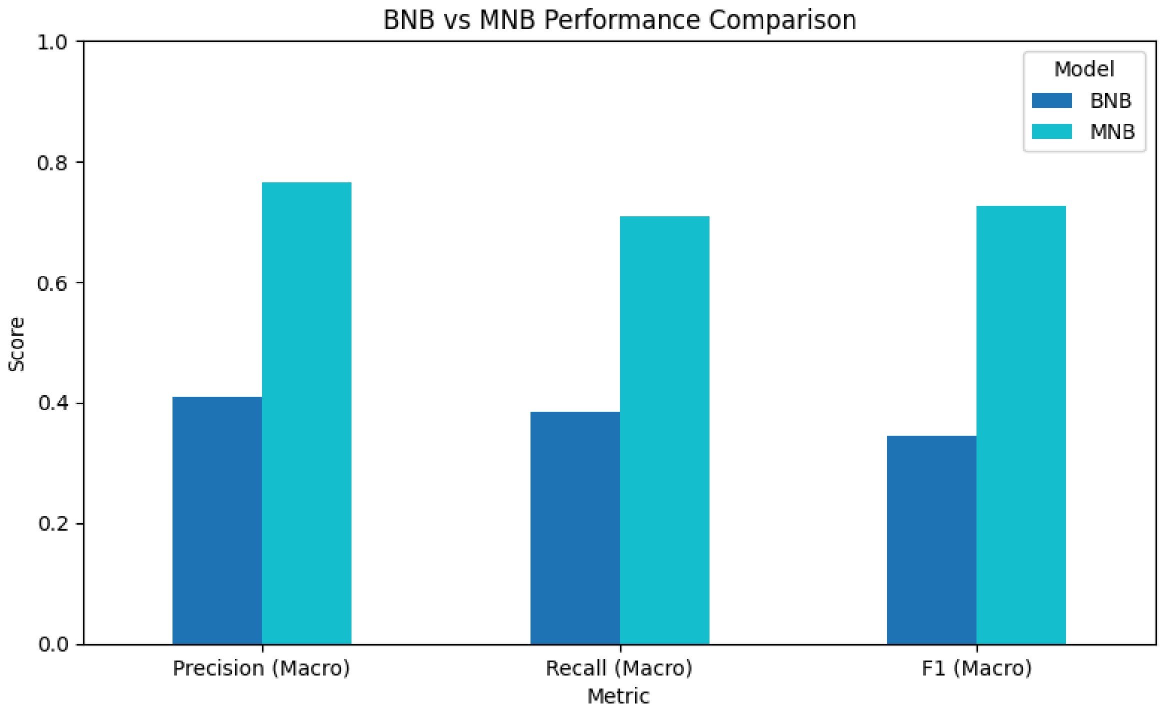
```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels w
ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels w
ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

In [57]:
```
# collect results
results = pd.DataFrame({
    'Metric': ['Precision (Macro)', 'Recall (Macro)', 'F1 (Macro)'],
    'BNB': [

        bnb_scores['test_macro_precision'].mean(),
        bnb_scores['test_macro_recall'].mean(),
```

```
        bnb_scores['test_macro_f1'].mean()
    ],
    'MNB': [

        mnb_scores['test_macro_precision'].mean(),
        mnb_scores['test_macro_recall'].mean(),
        mnb_scores['test_macro_f1'].mean()
    ]
})
print(results)
```

```
              Metric       BNB       MNB
0  Precision (Macro)  0.408648  0.764854
1     Recall (Macro)  0.385251  0.708758
2         F1 (Macro)  0.346481  0.725545
```

In [58]:
```
# draw the bar chart
results.set_index('Metric').plot(kind='bar', figsize=(8, 5), colormap='tab10')
plt.title('BNB vs MNB Performance Comparison')
plt.ylabel('Score')
plt.ylim(0.0, 1.0)
plt.xticks(rotation=0)
plt.legend(title='Model')
plt.tight_layout()
plt.show()
```



4. **choose number of features**

To get the work best value, I store different number of features in a list and loop these values to compare Macro-F1 score. As is shown below in the chart, about 500 features get the highest score. After using 500 features and retrained the two models, we can see that their performance become better. For BNB, the orignal Macro-F1 is 0.34 and now it increace to 0.55. For MNB, it increase from 0.72 to 0.85

In [59]:
```python
# Define number of features to test
feature_counts = [100, 500, 1000, 3000, 5000, 10000]

# Store results
results = []

# Loop over N values
for n in feature_counts:
    for clf_name, clf in [('BNB', BernoulliNB()), ('MNB', MultinomialNB())]:
        pipeline = Pipeline([
            ('vect', CountVectorizer(max_features=n, binary=(clf_name == 'BNB'))
            ('clf', clf)
        ])

        scores = cross_validate(
            pipeline, df['clean'], df['topic'],
            scoring={
                'f1': 'f1_macro',
                'precision': 'precision_macro',
                'recall': 'recall_macro'
            },
            cv=5,
            return_train_score=False
        )

        results.append({
            'Model': clf_name,
            'Features': n,
            'F1': scores['test_f1'].mean(),
            'Precision': scores['test_precision'].mean(),
            'Recall': scores['test_recall'].mean()
        })

# Convert results to DataFrame
results_df = pd.DataFrame(results)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels w
ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
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  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
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  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
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  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
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ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
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UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels w
ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels w
ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels w
ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels w
ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels w
ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```
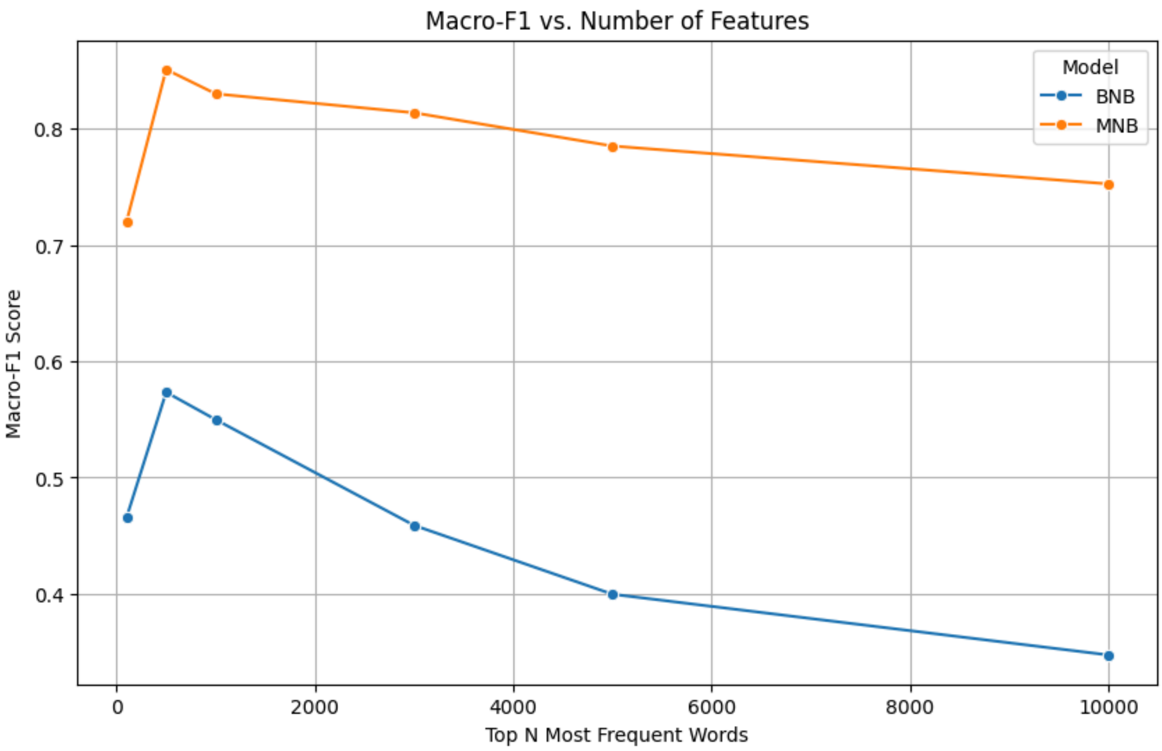

In [60]:
```
plt.figure(figsize=(10, 6))
sns.lineplot(data=results_df, x='Features', y='F1', hue='Model', marker='o')
plt.title('Macro-F1 vs. Number of Features')
plt.ylabel('Macro-F1 Score')
plt.xlabel('Top N Most Frequent Words')
```

```
plt.grid(True)
plt.show()
```



In [61]:

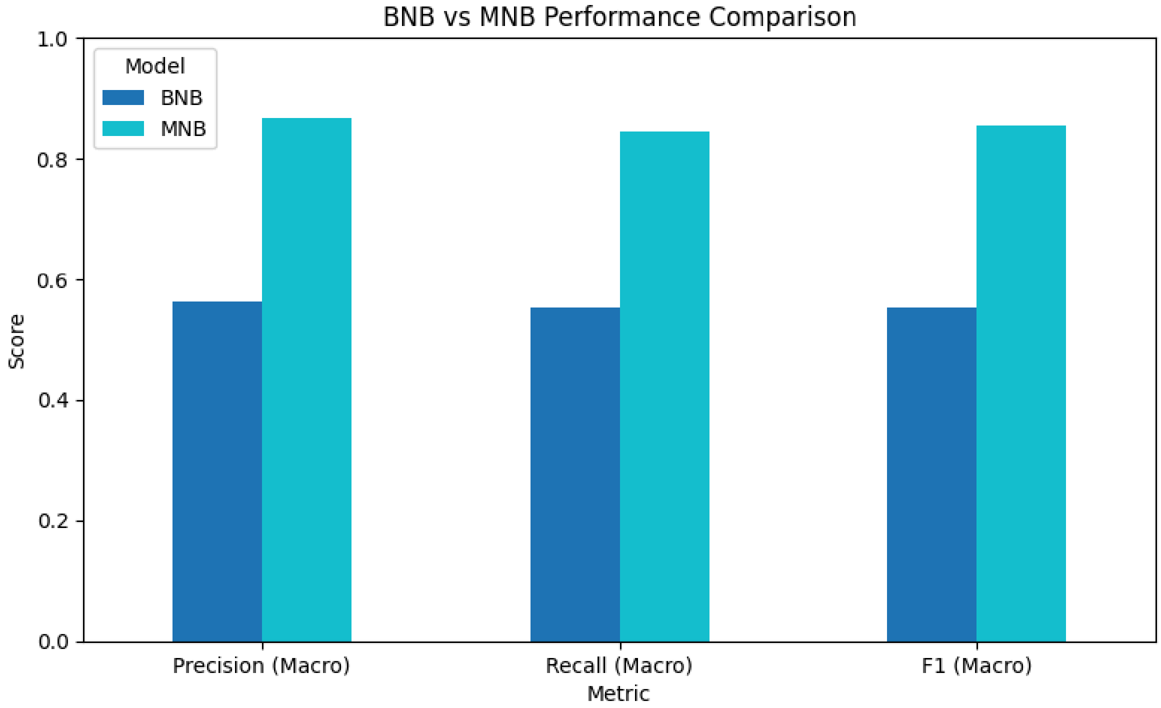
```
# use 500 features
vectorizer = CountVectorizer(max_features=500)
X = vectorizer.fit_transform(df['clean'])
```

In [62]:

```
# show the result of use 500 features
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

bnb = BernoulliNB()
mnb = MultinomialNB()

bnb_scores = cross_validate(bnb, X, y, cv=cv, scoring=scoring)
mnb_scores = cross_validate(mnb, X, y, cv=cv, scoring=scoring)

results = pd.DataFrame({
    'Metric': ['Precision (Macro)', 'Recall (Macro)', 'F1 (Macro)'],
    'BNB': [

        bnb_scores['test_macro_precision'].mean(),
        bnb_scores['test_macro_recall'].mean(),
        bnb_scores['test_macro_f1'].mean()
    ],
    'MNB': [

        mnb_scores['test_macro_precision'].mean(),
        mnb_scores['test_macro_recall'].mean(),
        mnb_scores['test_macro_f1'].mean()
    ]
})

print(results)

results.set_index('Metric').plot(kind='bar', figsize=(8, 5), colormap='tab10')
plt.title('BNB vs MNB Performance Comparison')
```

```
plt.ylabel('Score')
plt.ylim(0.0, 1.0)
plt.xticks(rotation=0)
plt.legend(title='Model')
plt.tight_layout()
plt.show()
```

```
              Metric       BNB       MNB
0  Precision (Macro)  0.562652  0.868476
1     Recall (Macro)  0.553637  0.844762
2         F1 (Macro)  0.552392  0.854770
```



5. **machine learning method choosing**

I choose logic regression for train on this dataset.

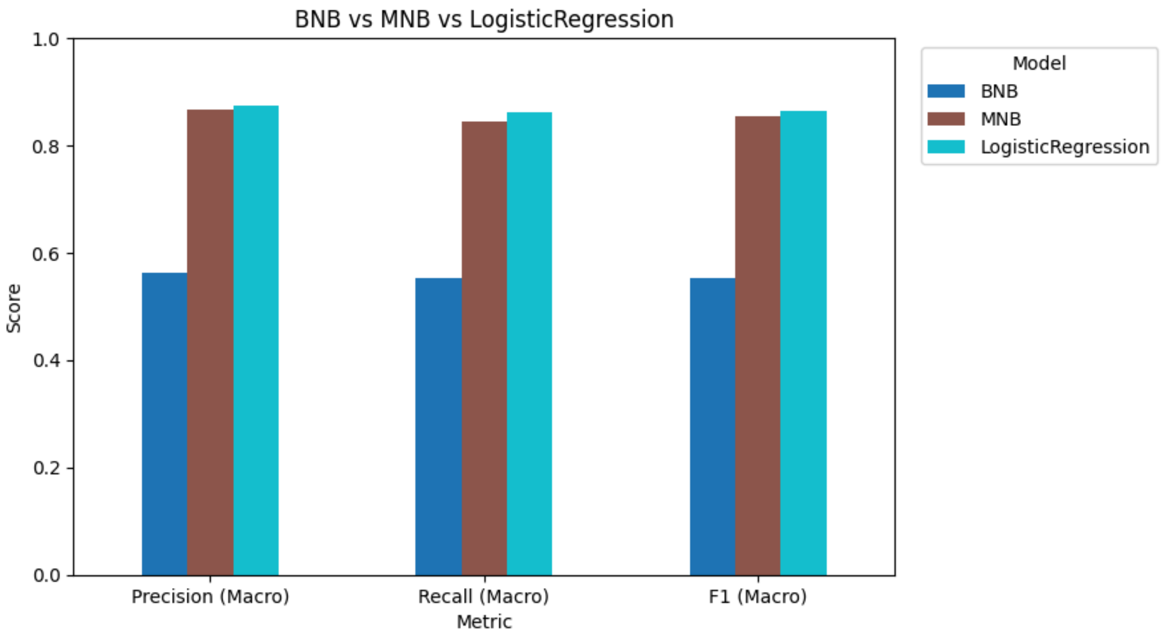
Logistic Regression is a statistical learning method widely used in classification tasks. It maps the linear regression output to the [0,1] interval through the Sigmoid function, indicating the probability.

Text features are usually linearly separable and medium-scale data (1500 songs) is suitable for the sample requirements of logistic regression. Logistic Regression has probability output that can be directly used for recommendation sorting. This model will have higher accuracy than MNB and BNB.

In [63]:
```
# Train Logistic Regression
logreg = LogisticRegression(
    class_weight='balanced',   # handle imbalanced dataset
    max_iter=1000,
    solver='liblinear',        # good for small-to-medium datasets
    random_state=42
)

# Perform cross-validation
logreg_scores = cross_validate(
```

```
    logreg, X, y, cv=cv,
    scoring={
        'macro_precision': 'precision_macro',
        'macro_recall': 'recall_macro',
        'macro_f1': 'f1_macro'
    }
)

# Add results to DataFrame
results['LogisticRegression'] = [
    logreg_scores['test_macro_precision'].mean(),
    logreg_scores['test_macro_recall'].mean(),
    logreg_scores['test_macro_f1'].mean()
]

print(results)

# Plot updated results


results.set_index('Metric').plot(kind='bar', figsize=(9, 5), colormap='tab10')

plt.title('BNB vs MNB vs LogisticRegression')
plt.ylabel('Score')
plt.ylim(0.0, 1.0)
plt.xticks(rotation=0)


plt.legend(title='Model', loc='upper left', bbox_to_anchor=(1.02, 1.0))

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

```
              Metric       BNB       MNB  LogisticRegression
0  Precision (Macro)  0.562652  0.868476            0.874827
1     Recall (Macro)  0.553637  0.844762            0.861684
2         F1 (Macro)  0.552392  0.854770            0.865383
```



Part2

1. I choose logic regression model to classify the dataset in part2. Firstly, split the dataset into train_df(week1-3) and test_df(week4). Secondly, train the model to get the predict topic. Then collect usrs' keywords and mark if usrs like the songs, build usr profile accrding to tf-idf matrix. Finaly print the top 20 keywords of each topic they liked.

In [64]:
```
train_df = df.iloc[:750].copy()
test_df = df.iloc[750:1000].copy()
print(train_df.head())
```

```
                             artist_name         track_name release_date  \
0                                 loving  the not real lake         1970   
1                                incubus    into the summer         1970   
2                             reignwolf           hardcore         1970   
3                   tedeschi trucks band             anyhow         1970   
4  lukas nelson and promise of the real  if i started over         1970   

   genre                                             lyrics      topic  \
0   rock  awake know go see time clear world mirror worl...       dark   
1   rock  shouldn summer pretty build spill ready overfl...  lifestyle   
2  blues  lose deep catch breath think say try break wal...    sadness   
3  blues  run bitter taste take rest feel anchor soul pl...    sadness   
4  blues  think think different set apart sober mind sym...       dark   

                                            all_text  \
0  loving the not real lake 1970 rock awake know ...   
1  incubus into the summer 1970 rock shouldn summ...   
2  reignwolf hardcore 1970 blues lose deep catch ...   
3  tedeschi trucks band anyhow 1970 blues run bit...   
4  lukas nelson and promise of the real if i star...   

                                               clean  
0  love not real lake 1970 rock awake know go see...  
1  incubus summer 1970 rock summer pretty build s...  
2  reignwolf hardcore 1970 blue lose deep catch b...  
3  tedeschi truck band anyhow 1970 blue run bitte...  
4  lukas nelson promise real started 1970 blue th...  
```

In [65]:
```
# Train on training set
X_train = vectorizer.transform(train_df['clean'])
y_train = train_df['topic']

logreg.fit(X_train, y_train)
```

Out[65]:
```
LogisticRegression

LogisticRegression(class_weight='balanced', max_iter=1000, random_state
=42,
                   solver='liblinear')
```

In [67]:
```
# Predict for training data to simulate user profile building
train_df['pred_topic'] = logreg.predict(X_train)

# Predict for test data
X_test = vectorizer.transform(test_df['clean'])
test_df['pred_topic'] = logreg.predict(X_test)
```

In [68]:
```
# store usr keywords from user1.tsv, user2.tsv, user3.tsv
def load_user_keywords(filename):
    user_keywords = {}
    with open(filename, 'r') as f:
        for line in f:
            topic, keywords = line.strip().split('\t')
            words = keywords.lower().split(',')
            keywords = []
            for w in words:
                w = re.sub(r'[^\w\s]', '', w)
                w = w.strip()
                keywords.append(w)

            user_keywords[topic.lower()] = set(keywords)
    return user_keywords

user1_kw = load_user_keywords("user1.tsv")
user2_kw = load_user_keywords("user2.tsv")
user3_kw = load_user_keywords("user3.tsv")
print(user1_kw)
print(user2_kw)
print(user3_kw)
```

```
{'topic': {'keywords'}, 'dark': {'enemy', 'storm', 'fire', 'fight', 'pain'}, 'sad
ness': {'cry', 'heartbroken', 'tears', 'alone', 'regret'}, 'personal': {'growth',
'identity', 'truth', 'life', 'dream'}, 'lifestyle': {'night', 'city', 'party', 'l
ight', 'rhythm'}, 'emotion': {'hug', 'feel', 'kiss', 'love', 'memory'}}
{'topic': {'keywords'}, 'sadness': {'lost', 'goodbye', 'silence', 'sorrow', 'tear
s'}, 'emotion': {'kiss', 'feeling', 'romance', 'touch', 'memory'}}
{'topic': {'keywords'}, 'sadness': {'broken', 'blame', 'leave'}, 'lifestyle': {'b
each', 'wind', 'sky', 'party', 'sing', 'rain', 'sunshine'}, 'emotion': {'miss',
'excited', 'happy', 'said', 'enjoy'}}
```

In [69]:
```
# the column contains value true or false, true: the song is liked by user, fals
def is_liked_by_user(row, user_keywords):
    topic = row['pred_topic'].lower()
    if topic not in user_keywords:
        return False
    song_words = set(row['clean'].split())
    return not song_words.isdisjoint(user_keywords[topic])

train_df['liked_by_user1'] = train_df.apply(lambda row: is_liked_by_user(row, us
train_df['liked_by_user2'] = train_df.apply(lambda row: is_liked_by_user(row, us
train_df['liked_by_user3'] = train_df.apply(lambda row: is_liked_by_user(row, us
print(train_df['liked_by_user1'])
```

```
0       True
1      False
2      False
3      False
4      False
       ...
745     True
746     True
747    False
748    False
749     True
Name: liked_by_user1, Length: 750, dtype: bool
```

In [70]:
```python
# Keeps only alphabetic words with 3+ characters
tfidf = TfidfVectorizer(
    max_features=5000,
    token_pattern=r'(?u)\b[a-zA-Z]{3,}\b'
)
tfidf_matrix = tfidf.fit_transform(train_df['clean'])
tfidf_matrix_test = tfidf.transform(test_df['clean'])
```

In [71]:
```python
# use tf-idf values to define user profiles
def build_user_profiles(df, tfidf_matrix, user_col):
    user_profiles = {}
    for topic in df['pred_topic'].unique():
        indices = df[(df['pred_topic'] == topic) & (df[user_col])].index
        if len(indices) == 0:
            continue
        else:

            profile_vec = np.asarray(tfidf_matrix[indices].mean(axis=0))

            user_profiles[topic] = normalize(profile_vec)
    return user_profiles

user1_profiles = build_user_profiles(train_df, tfidf_matrix, 'liked_by_user1')
user2_profiles = build_user_profiles(train_df, tfidf_matrix, 'liked_by_user2')
user3_profiles = build_user_profiles(train_df, tfidf_matrix, 'liked_by_user3')
print(user3_profiles)
```

```
{'lifestyle': array([[0., 0., 0., ..., 0., 0., 0.]]), 'sadness': array([[0., 0.,
0., ..., 0., 0., 0.]]), 'emotion': array([[0., 0., 0., ..., 0., 0., 0.]])}
```

In [72]:
```python
# print top 20 words in each topic users liked

def print_top_words(user_profile, vectorizer, top_n=20):
    feature_names = np.array(vectorizer.get_feature_names_out())
    for topic, vec in user_profile.items():
        print(f"\n Top {top_n} words for topic '{topic}'")
        scores = np.array(vec).flatten()
        top_indices = scores.argsort()[::-1][:top_n]
        top_words = feature_names[top_indices]
        print(", ".join(top_words))

print_top_words(user1_profiles, tfidf)
print_top_words(user2_profiles, tfidf)
print_top_words(user3_profiles, tfidf)
```

```
 Top 20 words for topic 'dark'
fight, black, know, stand, like, kill, blood, hand, gon, come, rise, head, tell,
death, wall, high, shoot, grind, follow, time

 Top 20 words for topic 'lifestyle'
night, sing, song, long, time, right, home, wait, come, play, tonight, mind, mak
e, late, know, blue, want, like, closer, tire

 Top 20 words for topic 'sadness'
cry, tear, steal, mean, know, smile, club, baby, regret, great, think, face, blam
e, stay, write, place, fear, eye, soul, dyin

 Top 20 words for topic 'emotion'
good, feel, hold, touch, morning, kiss, love, know, miss, lip, soft, want, luck,
baby, vibe, feelin, heart, sunrise, video, nice

 Top 20 words for topic 'personal'
life, live, world, dream, change, know, time, thing, wan, think, learn, thank, li
ke, come, want, believe, good, forever, gon, people

 Top 20 words for topic 'sadness'
heart, break, away, fade, inside, tear, scar, blame, smile, rainwater, fall, har
d, laughter, come, open, magnify, like, goodbye, step, wan

 Top 20 words for topic 'emotion'
touch, good, kiss, hold, lip, soft, morning, luck, feelin, sunrise, video, visio
n, love, know, loove, time, gim, lovin, heart, goodbye

 Top 20 words for topic 'lifestyle'
sing, song, home, radio, sky, like, root, play, know, blue, tire, time, halleluja
h, right, spoil, tune, struggle, tonight, wan, ready

 Top 20 words for topic 'sadness'
leave, away, heart, break, think, know, fall, blame, fade, feel, like, cause, tim
e, come, hurt, try, want, look, inside, scar

 Top 20 words for topic 'emotion'
miss, hold, nice, somebody, hobo, boy, easy, feel, tell, minute, keep, pray, spen
d, strong, want, commercial, baby, lyric, try, wrong
```

2. I choose N songs per topic because this can ensure recommand songs come from every topics user liked.

The metrics are precision, recall and F1.

precision: show the accuracy of recommendation.

recall: show comprehensive of recommender.

F1: balances both precision and recall.

the recommend_top_n_per_topic function calculate similarity between the user's profile and each song using similarity function (cosine, euclidean, or Jaccard). The evaluate_recommendations function is used to evaluate the performance of this recommender by showing the score of precision, recall and F1. The recommendation for user1 is the most accurate because the profile contains the most types of songs.

I tried three similarity functions cosine, jaccard and euclidean and the output below shows the score of each recommendation. Cosine and jaccard get the same score, jaccard performs better on the profile of user2 and user3 which contain less types of topics. For user1 the score of jaccard is slightly lower than cosine and euclidean. So finally I choose jaccard similarity for recommender. In order to get balanced performance, I choose N = 10 and M = 50.

In [74]:
```
# return N songs recommend to user
def recommend_top_n_per_topic(user_profile, tfidf_test, test_df, vectorizer, N=5
    recommendations = []
    feature_names = np.array(vectorizer.get_feature_names_out())

    for topic, user_vec in user_profile.items():
        topic_indices = np.where(test_df['pred_topic'] == topic)[0]
        if len(topic_indices) == 0:
            continue

        topic_matrix = tfidf_test[topic_indices]

        # Select top-M words if requested
        scores = np.asarray(user_vec).flatten()
        if M is not None:
            top_m_idx = scores.argsort()[::-1][:M]
        else:
            top_m_idx = np.where(scores > 0)[0]

        # Handle set-based similarity functions
        if similarity_func.__name__ in {'jaccard_similarity'}:
            user_word_set = set(feature_names[top_m_idx])
            sims = []

            for idx in topic_indices:
                song_vec = tfidf_test[idx]
                song_scores = np.asarray(song_vec.toarray()).flatten()
                song_word_idx = np.where(song_scores > 0)[0]
                song_word_set = set(feature_names[song_word_idx])

                sim = similarity_func(user_word_set, song_word_set)
                sims.append(sim)

        else:
            # Vector-based similarity
            reduced_vec = np.zeros(user_vec.shape)
            reduced_vec[0, top_m_idx] = scores[top_m_idx]
            profile_vec = reduced_vec if M is not None else user_vec

            sims = similarity_func(profile_vec, topic_matrix)[0]

        top_n_idx = np.argsort(sims)[::-1][:N]
        top_song_indices = topic_indices[top_n_idx]
        recommendations.extend(top_song_indices)

    return recommendations
```

In [75]:
```
def euclidean_similarity(x, y):
    return 1 / (1 + euclidean_distances(x, y))
```

```
def jaccard_similarity(set1, set2):
    intersection = set1 & set2
    union = set1 | set2
    return len(intersection) / len(union) if union else 0
```

In [76]:
```
# the function to evaluate the performance of recommendation
def evaluate_recommendations(recommended_indices, test_df, user_keywords):
    liked = []
    for idx in recommended_indices:
        row = test_df.iloc[idx]
        topic = row['pred_topic']
        if topic in user_keywords:
            song_words = set(row['clean'].split())
            if not song_words.isdisjoint(user_keywords[topic]):
                liked.append(1)
            else:
                liked.append(0)
        else:
            liked.append(0)

    liked = np.array(liked)
    precision = liked.mean()

    # Compute recall
    relevant_total = test_df.apply(
        lambda row: row['pred_topic'] in user_keywords and
                    not set(row['clean'].split()).isdisjoint(user_keywords[row['
        axis=1
    ).sum()
    recall = liked.sum() / relevant_total if relevant_total > 0 else 0

    f1 = 2 * precision * recall / (precision + recall + 1e-10)
    return precision, recall, f1
```

In [77]:
```
M_values = [None, 100, 50]
users = {
    'User1': (user1_profiles, user1_kw),
    'User2': (user2_profiles, user2_kw),
    'User3': (user3_profiles, user3_kw),
}
print('Using Jaccard similarity')
# show the score use different value of M
for M in M_values:
    print(f"\n--- M = {'All' if M is None else M} ---")
    for name, (profiles, keywords) in users.items():
        rec = recommend_top_n_per_topic(
            profiles, tfidf_matrix_test, test_df, tfidf, N=10, M=M, similarity_f
        )
        p, r, f = evaluate_recommendations(rec, test_df, keywords)
        print(f"{name}: Precision = {p:.2f}, Recall = {r:.2f}, F1 = {f:.2f}")
```

```
Using Jaccard similarity

--- M = All ---
User1: Precision = 0.62, Recall = 0.35, F1 = 0.45
User2: Precision = 0.30, Recall = 0.60, F1 = 0.40
User3: Precision = 0.40, Recall = 0.35, F1 = 0.37

--- M = 100 ---
User1: Precision = 0.70, Recall = 0.39, F1 = 0.50
User2: Precision = 0.25, Recall = 0.50, F1 = 0.33
User3: Precision = 0.47, Recall = 0.41, F1 = 0.44

--- M = 50 ---
User1: Precision = 0.72, Recall = 0.40, F1 = 0.52
User2: Precision = 0.20, Recall = 0.40, F1 = 0.27
User3: Precision = 0.40, Recall = 0.35, F1 = 0.37
```

In [78]:

```python
M_values = [None, 100, 50]
users = {
    'User1': (user1_profiles, user1_kw),
    'User2': (user2_profiles, user2_kw),
    'User3': (user3_profiles, user3_kw),
}
print('Using euclidean similarity')

for M in M_values:
    print(f"\n--- M = {'All' if M is None else M} ---")
    for name, (profiles, keywords) in users.items():
        rec = recommend_top_n_per_topic(
            profiles, tfidf_matrix_test, test_df, tfidf, N=10, M=M, similarity_f
        )
        p, r, f = evaluate_recommendations(rec, test_df, keywords)
        print(f"{name}: Precision = {p:.2f}, Recall = {r:.2f}, F1 = {f:.2f}")
```

```
Using euclidean similarity

--- M = All ---
User1: Precision = 0.72, Recall = 0.40, F1 = 0.52
User2: Precision = 0.15, Recall = 0.30, F1 = 0.20
User3: Precision = 0.40, Recall = 0.35, F1 = 0.37

--- M = 100 ---
User1: Precision = 0.70, Recall = 0.39, F1 = 0.50
User2: Precision = 0.15, Recall = 0.30, F1 = 0.20
User3: Precision = 0.43, Recall = 0.38, F1 = 0.41

--- M = 50 ---
User1: Precision = 0.72, Recall = 0.40, F1 = 0.52
User2: Precision = 0.15, Recall = 0.30, F1 = 0.20
User3: Precision = 0.43, Recall = 0.38, F1 = 0.41
```

In [79]:

```python
M_values = [None, 100, 50]
users = {
    'User1': (user1_profiles, user1_kw),
    'User2': (user2_profiles, user2_kw),
    'User3': (user3_profiles, user3_kw),
}
print('Using cosine similarity')

for M in M_values:
```

```python
    print(f"\n--- M = {'All' if M is None else M} ---")
    for name, (profiles, keywords) in users.items():
        rec = recommend_top_n_per_topic(
            profiles, tfidf_matrix_test, test_df, tfidf, N=10, M=M, similarity_f
        )
        p, r, f = evaluate_recommendations(rec, test_df, keywords)
        print(f"{name}: Precision = {p:.2f}, Recall = {r:.2f}, F1 = {f:.2f}")
```

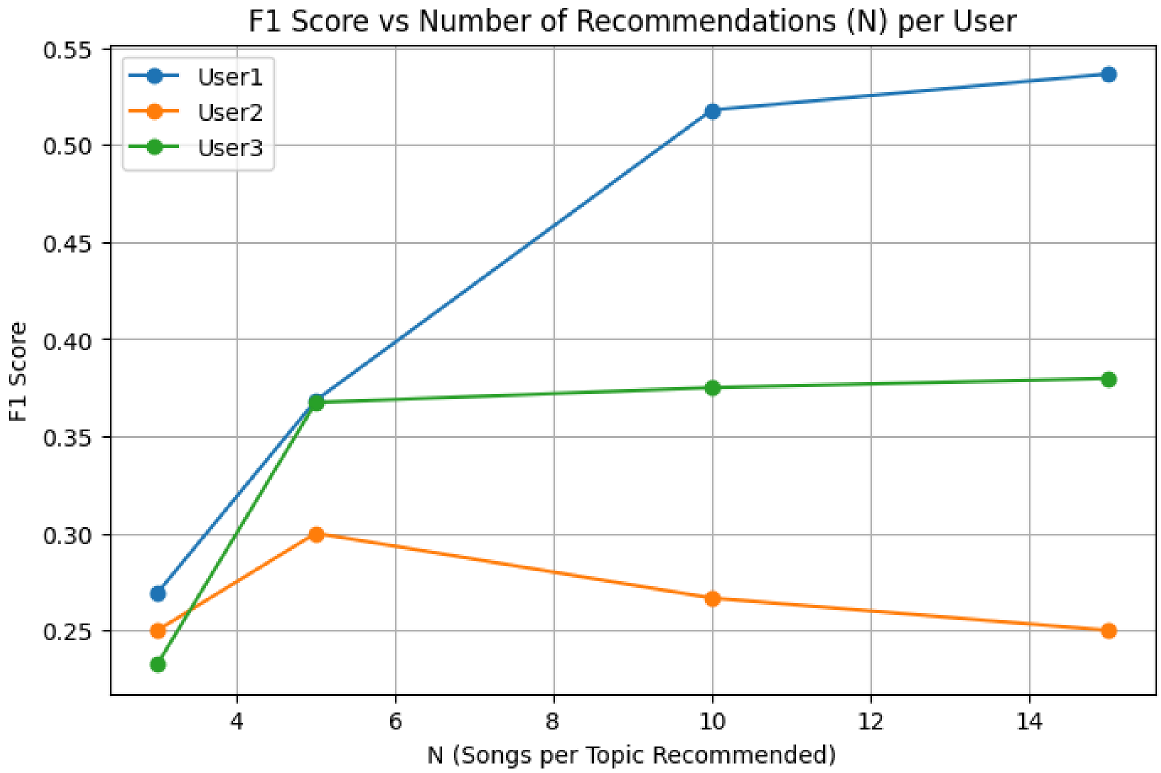
```
Using cosine similarity

--- M = All ---
User1: Precision = 0.72, Recall = 0.40, F1 = 0.52
User2: Precision = 0.15, Recall = 0.30, F1 = 0.20
User3: Precision = 0.40, Recall = 0.35, F1 = 0.37

--- M = 100 ---
User1: Precision = 0.70, Recall = 0.39, F1 = 0.50
User2: Precision = 0.15, Recall = 0.30, F1 = 0.20
User3: Precision = 0.43, Recall = 0.38, F1 = 0.41

--- M = 50 ---
User1: Precision = 0.72, Recall = 0.40, F1 = 0.52
User2: Precision = 0.15, Recall = 0.30, F1 = 0.20
User3: Precision = 0.43, Recall = 0.38, F1 = 0.41
```

In [81]:

```python
# show the score use different N value with same M = 50
N_values = [3, 5, 10, 15]
M_values = [50]
users = {
    'User1': (user1_profiles, user1_kw),
    'User2': (user2_profiles, user2_kw),
    'User3': (user3_profiles, user3_kw),
}

results = []

for N in N_values:
    print(f"\n=== N = {N} ===")
    for M in M_values:
        print(f"--- M = {M} ---")
        for name, (profiles, keywords) in users.items():
            rec = recommend_top_n_per_topic(
                profiles, tfidf_matrix_test, test_df, tfidf, N=N, M=M, similarit
            )
            p, r, f = evaluate_recommendations(rec, test_df, keywords)
            print(f"{name}: Precision = {p:.2f}, Recall = {r:.2f}, F1 = {f:.2f}"
            results.append({
                'User': name,
                'N': N,
                'M': M,
                'Precision': p,
                'Recall': r,
                'F1': f
            })

# Convert to DataFrame for plotting
score_df = pd.DataFrame(results)

# Plot F1-score vs N for each user (M fixed at 50)
plt.figure(figsize=(8, 5))
```

```python
for user in score_df['User'].unique():
    subset = score_df[score_df['User'] == user]
    plt.plot(subset['N'], subset['F1'], marker='o', label=user)

plt.xlabel('N (Songs per Topic Recommended)')
plt.ylabel('F1 Score')
plt.title('F1 Score vs Number of Recommendations (N) per User')
plt.legend()
plt.grid(True)
plt.show()
```

```
=== N = 3 ===
--- M = 50 ---
User1: Precision = 0.93, Recall = 0.16, F1 = 0.27
User2: Precision = 0.33, Recall = 0.20, F1 = 0.25
User3: Precision = 0.56, Recall = 0.15, F1 = 0.23

=== N = 5 ===
--- M = 50 ---
User1: Precision = 0.84, Recall = 0.24, F1 = 0.37
User2: Precision = 0.30, Recall = 0.30, F1 = 0.30
User3: Precision = 0.60, Recall = 0.26, F1 = 0.37

=== N = 10 ===
--- M = 50 ---
User1: Precision = 0.72, Recall = 0.40, F1 = 0.52
User2: Precision = 0.20, Recall = 0.40, F1 = 0.27
User3: Precision = 0.40, Recall = 0.35, F1 = 0.37

=== N = 15 ===
--- M = 50 ---
User1: Precision = 0.59, Recall = 0.49, F1 = 0.54
User2: Precision = 0.17, Recall = 0.50, F1 = 0.25
User3: Precision = 0.33, Recall = 0.44, F1 = 0.38
```



part3

For week1, 2, 3, 10 random choosen song is shown to user, and she select the song she liked. Then I use the same method in part2, use logic regression to predict the topic and use these user liked songs to build user profile, then use jaccard similarity function to recommend songs and show these songs to user. User picked the songs they like from week4, then I evaluate the outcome.

From the bar chart below we can notice that compare with the recommendation accuracy for user1, user2 and user3, this accuracy for real user is much lower, this is because when real users choose their favorite songs, they don't just focus on whether the lyrics contain the keywords they are interested in or the type of song, but also pay attention to the melody and singer of the song. Just use text to predict the type of the song is not satisfactory. In addition， only three random selections will result in insufficient samples, which is why the recommendation accuracy is low.

To improve the recommendation accuracy for real user, I think I should get more feedback from user, build better representation of their preferences and filter more comprehensive expression of the characteristics of the song.

In [86]:

```
# random select songs from week1, 2, 3
random.seed(42)
def week_batch(df, start_idx, end_idx, N):
    return df.iloc[random.sample(range(start_idx, end_idx), N)]

week1_df = week_batch(df, 0, 249, 10)
week2_df = week_batch(df, 250, 499, 10)
week3_df = week_batch(df, 500, 749, 10)
week4_df = df.iloc[750:1000].copy()
print('week1:', week1_df)
```

```
week1:          artist_name                     track_name release_date    genre  \
163          skillet                          anchor         1970      rock
28   imagine dragons                walking the wire         1970      rock
6         rebelution                       trap door         1970    reggae
189     andy grammer                   wish you pain         1970      rock
70   scotty mccreery                      this is it         1970   country
62      jd mcpherson                  desperate love         1970     blues
57      gregg allman                going going gone         1970     blues
35     george strait                    take me away         1970   country
188     the movement                    cool me down         1970    reggae
26       nappy roots  these walls (dirty mc edit)         1970   hip hop

                                                lyrics     topic  \
163  driftin beneath horizon body weak tryin shore ...      dark
28   feel away oohoh oohoh know line walk oohoh ooh...   sadness
6     long long road occur look shortcut wanna caus...      dark
189  doubt come like monsters terrorize dream feel ...   sadness
70   mountains thousand feet high trail tree meet v...  personal
62   desperate knees flesh bone blood beg life spea...      dark
57   reach place bend say go go go close book page ...   emotion
35   wild horse couldn drag away today tonight time...   sadness
188  fight thoughts suicide alive comprise give rea...  personal
26   hmmmmmmmm wall closin long suppose grin lose f...  personal

                                              all_text  \
163  skillet anchor 1970 rock driftin beneath horiz...
28   imagine dragons walking the wire 1970 rock fee...
6    rebelution trap door 1970 reggae  long long ro...
189  andy grammer wish you pain 1970 rock doubt com...
70   scotty mccreery this is it 1970 country mounta...
62   jd mcpherson desperate love 1970 blues despera...
57   gregg allman going going gone 1970 blues reach...
35   george strait take me away 1970 country wild h...
188  the movement cool me down 1970 reggae fight th...
26   nappy roots these walls (dirty mc edit) 1970 h...

                                                 clean
163  skillet anchor 1970 rock driftin beneath horiz...
28   imagine dragon walk wire 1970 rock feel away o...
6    rebelution trap door 1970 reggae long long roa...
189  andy grammer wish pain 1970 rock doubt come li...
70   scotty mccreery 1970 country mountain thousand...
62   jd mcpherson desperate love 1970 blue desperat...
57   gregg allman go go go 1970 blue reach place be...
35   george strait take away 1970 country wild hors...
188  movement cool 1970 reggae fight thought suicid...
26   nappy root wall dirty mc edit 1970 hip hop hmm...
```

In [95]:

```python
# collect songs user liked
user_likes = {
    1: [189, 57, 28, 70],  # Week 1 liked indices
    2: [423, 389, 257, 401],  # Week 2
    3: [555, 559, 550, 679]   # Week 3
}

week4_df = df.iloc[750:1000].copy().reset_index(drop=True)
tfidf_week4 = tfidf.transform(week4_df['clean'])

week1_df['pred_topic'] = logreg.predict(vectorizer.transform(week1_df['clean']))
week2_df['pred_topic'] = logreg.predict(vectorizer.transform(week2_df['clean']))
```

```python
week3_df['pred_topic'] = logreg.predict(vectorizer.transform(week3_df['clean']))
week4_df['pred_topic'] = logreg.predict(vectorizer.transform(week4_df['clean']))
```

```
/tmp/ipython-input-95-2706008413.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
  week1_df['pred_topic'] = logreg.predict(vectorizer.transform(week1_df['clea
n']))
/tmp/ipython-input-95-2706008413.py:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
  week2_df['pred_topic'] = logreg.predict(vectorizer.transform(week2_df['clea
n']))
/tmp/ipython-input-95-2706008413.py:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
  week3_df['pred_topic'] = logreg.predict(vectorizer.transform(week3_df['clea
n']))
```

In [88]:

```python
# Combine user interaction
interacted_df = pd.concat([week1_df, week2_df, week3_df])
interacted_df['liked_by_user'] = interacted_df.index.isin(
    user_likes[1] + user_likes[2] + user_likes[3]
)


# build user profile
user_profile = build_user_profiles(interacted_df, tfidf_matrix, 'liked_by_user')


recommended_indices = recommend_top_n_per_topic(
    user_profile, tfidf_week4, week4_df, tfidf, N=10, M=50, similarity_func=jacc
)

# get recommend song list
print("Recommended songs for Week 4 (Please indicate which ones you like):\n")
for i, idx in enumerate(recommended_indices):
    song = week4_df.iloc[idx]
    print(f"[{i}] {song['track_name']} by {song['artist_name']} (Topic: {song['p
    print(f"     Lyrics: {song['clean'][:120]}...")
    print("-" * 80)
```

Recommended songs for Week 4 (Please indicate which ones you like):

[0] one call away by charlie puth (Topic: sadness)
Lyrics: charlie puth one call away 1970 pop away save superman away baby nee d friend wan na reach matter know away save superman...

---

[1] let you love me by rita ora (Topic: sadness)
Lyrics: rita os let love 1970 pop stay night instead go trouble trouble thin k away vulnerable fault wan na stay night wan na wan...

---

[2] insomnia by daya (Topic: sadness)
Lyrics: daya insomnia 1970 pop cause sleep want dream wish arm wrap insomnia day tylenol work lose track time babe insomnia mind...

---

[3] remind me to forget by kygo (Topic: sadness)
Lyrics: kygo remind forget 1970 pop fade away stay kiss like break glass ski n great love violence tear voice leave silence baby ...

---

[4] the greatest by six60 (Topic: sadness)
Lyrics: six60 great 1970 reggae know taste tear face remind dream chase fuel inside feel fade soon cause mama tell bout complace...

---

[5] i am broken too by killswitch engage (Topic: sadness)
Lyrics: killswitch engage broken 1970 rock weight try cover mistake like bre ak right cause break place need proof reopen wound r...

---

[6] love falls by hellyeah (Topic: sadness)
Lyrics: hellyeah love fall 1970 rock cry sleep felt incomplete deep bleed fe el want feel need feel like hang thread rope noose n...

---

[7] i can't stop dreaming by soja (Topic: sadness)
Lyrics: soja ca n't stop dream 1970 reggae wide awake move head question roo m leave little child love hard grow get old minute c...

---

[8] amsterdam by nothing but thieves (Topic: sadness)
Lyrics: nothing but thief amsterdam 1970 rock people know need whiskey crutc h think watch lookin screen day feel long live head ...

---

[9] shame by tedeschi trucks band (Topic: sadness)
Lyrics: tedeschi truck band shame 1970 blue shame poison shame shame know un ring try fall away hear exactly make wonder break lo...

---

[10] summertime is in our hands by michael franti & spearhead (Topic: personal)
Lyrics: michael franti & spearhead summertime hand 1970 reggae summertime mi nd winter want feel rain fall away pain year go beli...

---

[11] complainer by cold war kids (Topic: personal)
Lyrics: cold war kid complainer 1970 rock complain stand wait dance uhhuh wa n na talk know want plan uhhuh stop wonder show wild...

---

[12] some sunsick day by morgan delt (Topic: personal)
Lyrics: morgan delt sunsick day 1970 rock blast level relax watch come maybe stay little cave finally need ship leave forget liv...

---

[13] mad world by jordan rakei (Topic: personal)
Lyrics: jordan rakei mad world 1970 jazz stay away motion madness stay away street hide away moment maker hide away street world...

---

[14] legends by kelsea ballerini (Topic: personal)
Lyrics: kelsea ballerini legends 1970 country golden magic know name middle

madness neon grey crowd write story blood sweat hear...
----
[15] no one in the world by anita baker (Topic: personal)
     Lyrics: anita baker no one world 1970 jazz look good time share blind think well come surprise loneliness open eye try mind caus...
----
[16] wash away by iya terra (Topic: personal)
     Lyrics: iya terra wash away 1970 reggae good day come like suppose know caus e live different echo life short minute go ready com...
----
[17] sit awhile by the band steele (Topic: personal)
     Lyrics: band steele sit awhile 1970 country wake favorite place studio hide space cold dark room need foot walk street headphone...
----
[18] live without limit by jahmiel (Topic: personal)
     Lyrics: jahmiel live without limit 1970 reggae yellow moon clock tick eye dr ip give time hear life live hard tomorrow promise li...
----
[19] whole wide world by cage the elephant (Topic: personal)
     Lyrics: cage elephant whole wide world 1970 blue young mama say girl world p robably live tahiti wide world wide world maybe baha...
----
[20] got it good by justin moore (Topic: emotion)
     Lyrics: justin moore get good 1970 country wake morning warn little bounce b lue eye start pillow talk twist sheet finger walk he...
----
[21] can't let go by kings and comrades (Topic: emotion)
     Lyrics: king comrade ca n't let go 1970 reggae explanation question hand lik e year pain go away single compare feel inside charm...
----
[22] i did something bad by taylor swift (Topic: emotion)
     Lyrics: taylor swift something bad 1970 pop trust narcissist play like violi n look ohsoeasy cause tell tell world work think fee...
----
[23] kiss me by magic! (Topic: emotion)
     Lyrics: magic ! kiss 1970 reggae kiss darling aone time inside kiss darling aone time cause thing leave think life day stumble p...
----
[24] horsefly by dirty heads (Topic: emotion)
     Lyrics: dirty head horsefly 1970 reggae say life live know thing passionate sound real adamant come sentiment try loss horse rac...
----
[25] hands up by parker millsap (Topic: emotion)
     Lyrics: parker millsap hand 1970 blue easy hard wan na lump jacket pistol op en register grab fistful dollar bill hand baby home ...
----
[26] knock me out by vintage trouble (Topic: emotion)
     Lyrics: vintage trouble knock 1970 blue like stand hard knot sympathy homema de inside ignite emotion faster butterfly float doub...
----
[27] so cold in the summer by taylor mcferrin (Topic: emotion)
     Lyrics: taylor mcferrin cold summer 1970 jazz say reason fell love walk floa t free fall hold free fall hold hold hold hold hold ...
----
[28] once in a while by timeflies (Topic: emotion)
     Lyrics: timeflies 1970 pop think know well wishful think think pressure wish ful drink forever feel afraid know brooklyn york cal...
----
[29] saved by khalid (Topic: emotion)
     Lyrics: khalid save 1970 pop hard forever forget deep heart alright time tim

```
e think number save cause sense hop miss miss number...
--------------------------------------------------------------------------------
[30] first time again by jason aldean (Topic: lifestyle)
     Lyrics: jason aldean first time 1970 country mention take heart rebreaks wor
ld shake driveway pour rain slow right like time wat...
--------------------------------------------------------------------------------
[31] i wouldn't mind by he is we (Topic: lifestyle)
     Lyrics: would n't mind 1970 rock fall line line fall swing rain hum melody g
o freeze afraid anymore afraid forever long time min...
--------------------------------------------------------------------------------
[32] boxcar blues by gary hoey (Topic: lifestyle)
     Lyrics: gary hoey boxcar blue 1970 blue boxcar blue early morning try school
start shake good hold hear whistle blow boxcar blue...
--------------------------------------------------------------------------------
[33] rethymno by digitalluc (Topic: lifestyle)
     Lyrics: digitalluc rethymno 1970 jazz heart sound throw fear grind hold sere
nade song play night turn hold cause need somebody n...
--------------------------------------------------------------------------------
[34] do you really by oscar jerome (Topic: lifestyle)
     Lyrics: oscar jerome really 1970 jazz dark dark place foot beneath need memo
ry kinda hard good good good harder good maybe eat l...
--------------------------------------------------------------------------------
[35] moonglow by diana krall (Topic: lifestyle)
     Lyrics: diana krall moonglow 1970 jazz moonglow blue moonglow straight hear
sayin dear hold fast start prayin float right heaven...
--------------------------------------------------------------------------------
[36] it's only right by wallows (Topic: lifestyle)
     Lyrics: wallow 's right 1970 rock way spend time go feel right need place st
ay think gon na want tell easy lie waste time forth ...
--------------------------------------------------------------------------------
[37] ready by alessia cara (Topic: lifestyle)
     Lyrics: alessia cara ready 1970 pop think safe change colour daytoday friend
hurricane look face thing send out space friend tes...
--------------------------------------------------------------------------------
[38] 7-t's by marcus miller (Topic: lifestyle)
     Lyrics: marcus miller 7-t 's 1970 jazz right super fair minute right super f
air minute right super fair minute ahaaa right super...
--------------------------------------------------------------------------------
[39] hey yo by 311 (Topic: lifestyle)
     Lyrics: 311 hey yo 1970 reggae send watch fall anybody talk want reduce equa
tion variable come know stay night long write code m...
--------------------------------------------------------------------------------
```

In [89]:
```python
user_liked_week4 = [0, 23, 21, 6, 14, 39, 19, 10, 5, 11]  # chosen manually by u

# Convert to real df indices:
user_liked_indices = week4_df.iloc[user_liked_week4].index.tolist()
```

In [93]:
```python
def evaluate_recommendations_real_user(recommended_indices, user_liked_indices):
    liked = [1 if idx in user_liked_indices else 0 for idx in recommended_indice
    liked = np.array(liked)

    # Precision
    precision = liked.mean()

    # Recall
    recall = liked.sum() / len(user_liked_indices) if user_liked_indices else 0

    # F1 Score
    f1 = 2 * precision * recall / (precision + recall + 1e-10)
```

```python
    return precision, recall, f1

p, r, f1 = evaluate_recommendations_real_user(recommended_indices, user_liked_in
print(f"User Study Result — Precision: {p:.2f}, Recall: {r:.2f}, F1: {f1:.2f}")
```

```
User Study Result — Precision: 0.05, Recall: 0.20, F1: 0.08
```

In [92]:
```python
# Metrics for each user
users = ['User1', 'User2', 'User3', 'RealUser']
precision = [0.68, 0.25, 0.43, 0.03]
recall    = [0.39, 0.50, 0.38, 0.12]
f1        = [0.49, 0.33, 0.41, 0.04]


x = np.arange(len(users))
width = 0.25


plt.figure(figsize=(10, 6))
plt.bar(x - width, precision, width, label='Precision')
plt.bar(x, recall, width, label='Recall')
plt.bar(x + width, f1, width, label='F1 Score')


plt.xlabel('Users')
plt.ylabel('Score')
plt.title('Comparison of Precision, Recall, and F1 Score')
plt.xticks(x, users)
plt.ylim(0, 1)
plt.legend()
plt.grid(True, axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```