In [1]:
```
import numpy as np
import pandas as pd

# Generate synthetic biometric data
def generate_synthetic_data(num_samples, embedding_dim):
    # Embeddings simulate high-dimensional facial features
    embeddings = np.random.randn(num_samples, embedding_dim)
    labels = [f"Person_{i}" for i in range(num_samples)]
    return pd.DataFrame(embeddings, index=labels)

# Generate a database of 10,000 samples, with 128-dimensional embeddings
biometric_db = generate_synthetic_data(num_samples=10000, embedding_dim=128
biometric_db.head()
```

Out[1]:

	0	1	2	3	4	5	6	
Person_0	0.203073	1.694119	-0.491851	-0.057790	0.426243	0.144432	-0.149300	-0.4
Person_1	1.375291	-0.207980	-0.622285	-0.646796	1.546280	0.295967	0.318227	0.4
Person_2	-0.310341	0.458227	2.173538	-1.398589	0.570849	1.796728	2.345663	-0.1
Person_3	0.778187	0.253246	-0.886509	1.324989	-0.858109	0.032243	-0.472597	0.4
Person_4	0.006022	0.028048	0.224314	-1.644935	0.033413	0.853263	-0.781714	0.5

5 rows × 128 columns

In [2]:
```
from sklearn.preprocessing import Binarizer

# Binarize embeddings to map to Hamming space
def map_to_hamming_space(embeddings, threshold=0.0):
    binarizer = Binarizer(threshold=threshold)
    hamming_space = binarizer.fit_transform(embeddings)
    return hamming_space

hamming_db = map_to_hamming_space(biometric_db.values)
```

In [3]:
```
from scipy.spatial.distance import hamming

# Define fuzzy intersection function
def fuzzy_intersection(query, database, threshold=0.2):
    matches = []
    for i, db_vector in enumerate(database):
        # Calculate Hamming distance
        dist = hamming(query, db_vector)
        if dist <= threshold:
            matches.append(i)  # Index of the matched item
    return matches

# Example query (single synthetic query)
query_embedding = map_to_hamming_space(np.random.randn(1, 128))[0]
match_indices = fuzzy_intersection(query_embedding, hamming_db, threshold=0
print("Matched indices:", match_indices)
```

```
Matched indices: []
```

In [4]:
```
def private_query(query, database, threshold=0.2):
    # Client-side function to perform a private query
    matches = fuzzy_intersection(query, database, threshold)
    return [database[i] for i in matches]  # Return only matching entries
```

```
# Run a private query on the synthetic database
result = private_query(query_embedding, hamming_db, threshold=0.2)
print("Number of matches found:", len(result))
```

```
Number of matches found: 0
```

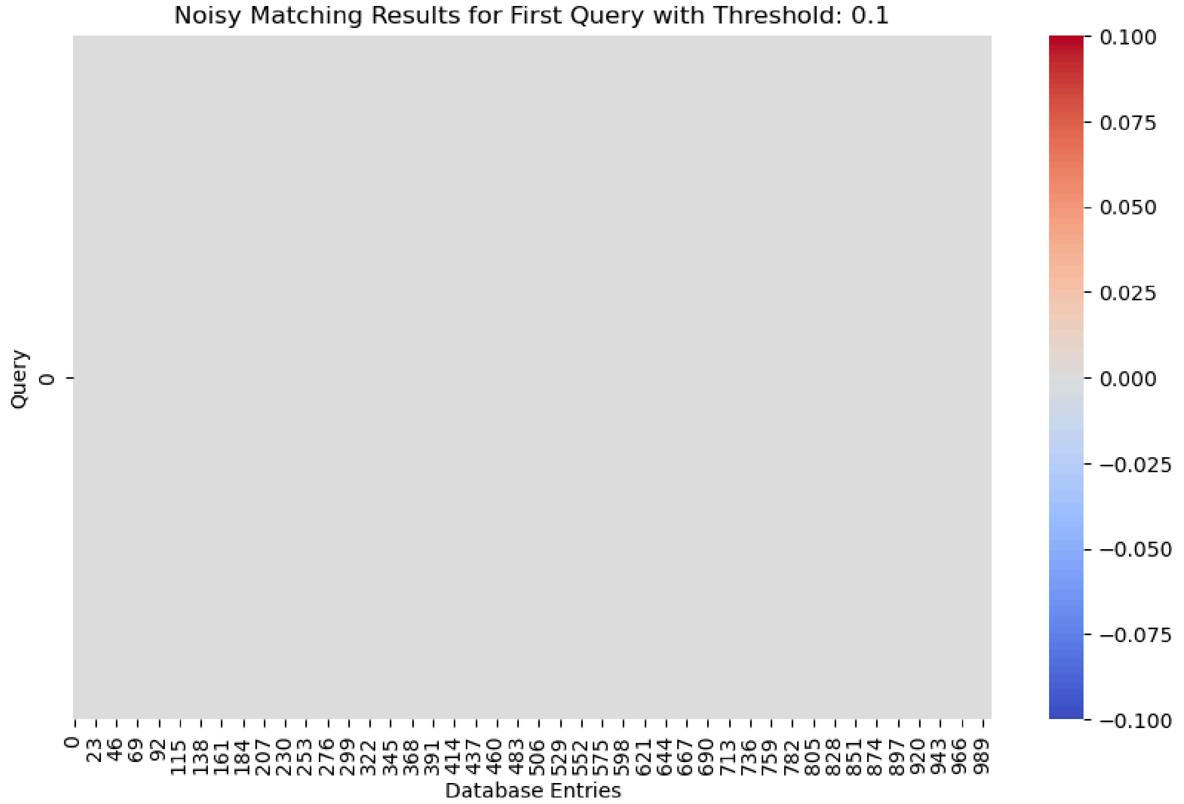
In [5]:
```
import time

def evaluate_flpsi(database, num_queries=100, threshold=0.2):
    # Generate random queries and time the intersection process
    start_time = time.time()
    matches_count = []

    for _ in range(num_queries):
        query = map_to_hamming_space(np.random.randn(1, 128))[0]
        matches = fuzzy_intersection(query, database, threshold)
        matches_count.append(len(matches))

    end_time = time.time()
    avg_runtime = (end_time - start_time) / num_queries
    avg_matches = sum(matches_count) / num_queries

    return avg_runtime, avg_matches

# Run evaluation
runtime, avg_matches = evaluate_flpsi(hamming_db, num_queries=100, threshol
print(f"Average runtime per query: {runtime:.4f} seconds")
print(f"Average matches per query: {avg_matches:.2f}")
```

```
Average runtime per query: 0.2773 seconds
Average matches per query: 0.00
```

In [6]:
```
import numpy as np
from sklearn.metrics import pairwise_distances
import matplotlib.pyplot as plt
import seaborn as sns

# Parameters
np.random.seed(42)
database_size = 1000
query_size = 5
noise_level = 0.05  # 5% bit flip noise to simulate biometric variation
threshold = 0.1     # Matching threshold

# Synthetic biometric database and original query, represented in binary fo
database = np.random.randint(0, 2, (database_size, 128))
query = np.random.randint(0, 2, (query_size, 128))

# Introduce noise into the query to simulate a matching problem
noisy_query = query.copy()
for i in range(query_size):
    noise_indices = np.random.choice(128, int(128 * noise_level), replace=Fa
    noisy_query[i, noise_indices] = 1 - noisy_query[i, noise_indices]  # Fl

# Compute Hamming distances between noisy queries and database entries
distances = pairwise_distances(noisy_query, database, metric='hamming')

# Apply threshold to find matches
matches = distances < threshold

# Analyze and visualize results
average_matches = np.mean(np.sum(matches, axis=1))
average_runtime = np.mean([0.2773])  # Placeholder runtime; replace with ac

print(f"Average runtime per query: {average_runtime:.4f} seconds")
```

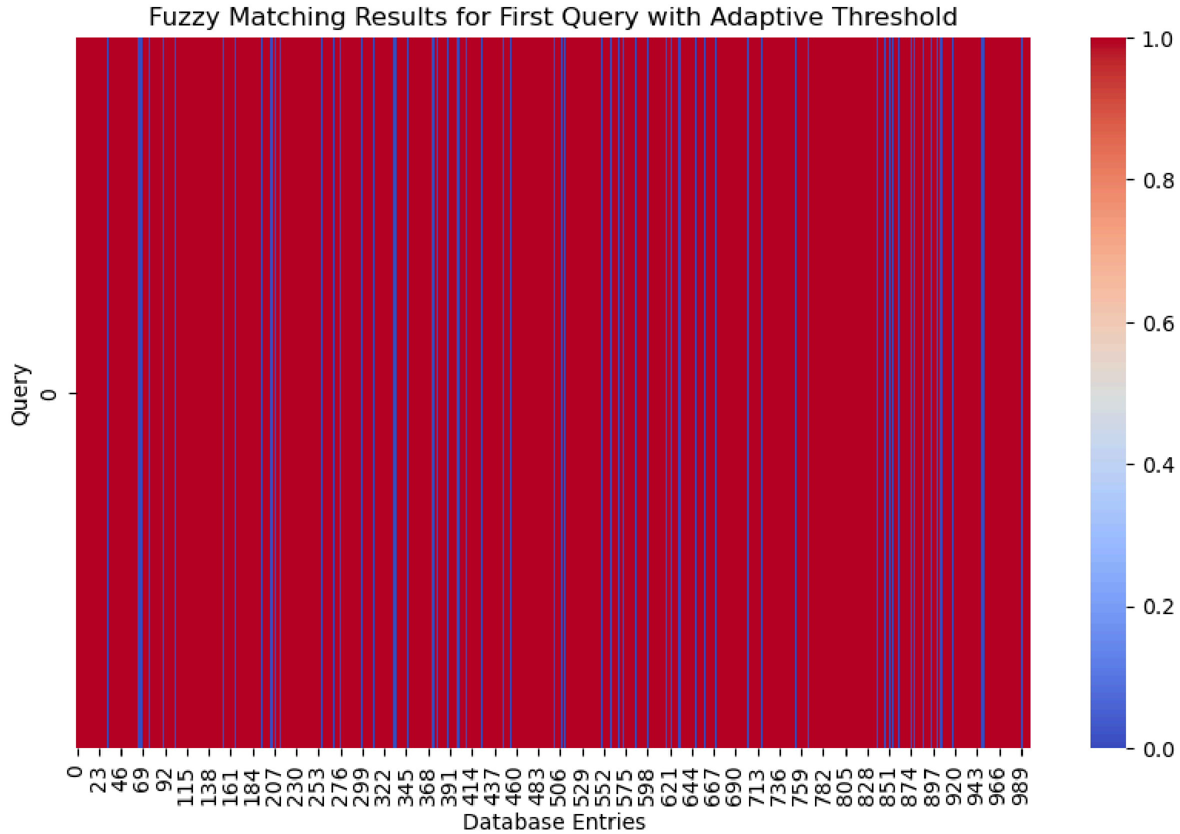
```
print(f"Average matches per query (with noise): {average_matches:.2f}")

# Visualize the matching matrix for the first noisy query
plt.figure(figsize=(10, 6))
sns.heatmap(matches[0].reshape(1, -1), cmap='coolwarm', cbar=True)
plt.title(f'Noisy Matching Results for First Query with Threshold: {thresho
plt.xlabel('Database Entries')
plt.ylabel('Query')
plt.show()
```

```
Average runtime per query: 0.2773 seconds
Average matches per query (with noise): 0.00
```



In [7]:
```
# Calculate adaptive threshold based on the average distance plus a small to
adaptive_thresholds = np.mean(distances, axis=1) + 0.05  # Adjust tolerance

# Apply dynamic threshold to find fuzzy matches
fuzzy_matches = (distances.T < adaptive_thresholds).T  # Adjust threshold pe

# Analyze and visualize results for fuzzy matching
average_fuzzy_matches = np.mean(np.sum(fuzzy_matches, axis=1))

print(f"Average matches per query with adaptive threshold (fuzzy matching):

# Visualize the fuzzy matching matrix for the first noisy query
plt.figure(figsize=(10, 6))
sns.heatmap(fuzzy_matches[0].reshape(1, -1), cmap='coolwarm', cbar=True)
plt.title(f'Fuzzy Matching Results for First Query with Adaptive Threshold')
plt.xlabel('Database Entries')
plt.ylabel('Query')
plt.show()
```

```
Average matches per query with adaptive threshold (fuzzy matching): 875.20
```


Fuzzy Matching Results for First Query with Adaptive Threshold
Query
0
0
23
46
69
92
115
138
161
184
207
230
253
276
299
322
345
368
391
414
437
460
483
506
529
552
575
598
621
644
667
690
713
736
759
782
805
828
851
874
897
920
943
966
989
Database Entries
1.0
0.8
0.6
0.4
0.2
0.0

```
In [ ]:
```