NETWORK ANALYSIS OF TRUST-BASED TRANSACTIONS IN THE BITCOIN OTC NETWORK

In [35]:
```
# Load the Libraires
import pandas as pd
import networkx as nx
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

Dataset Acquisition

In [8]:
```
# Load the dataset
data = pd.read_csv("soc-sign-bitcoinotc.csv.gz", compression='gzip', names=["sou

display(data.shape)
data.sample(10)
```

(35592, 4)

Out[8]:

	source	target	rating	timestamp
3198	782	784	1	1.306966e+09
22101	4163	4181	1	1.367124e+09
7567	353	1562	1	1.323376e+09
7433	1605	1566	2	1.322317e+09
17585	3202	1810	1	1.357695e+09
15785	2877	827	-1	1.352938e+09
29512	546	4038	-5	1.385849e+09
22323	4206	4198	2	1.367470e+09
23047	3445	1185	2	1.369196e+09
10266	2085	2088	1	1.337654e+09

Data Preprocessing

1. Format the dataset for network analysis - check for duplicates, convert the timestamp
2. Convert the dataset into a graph representation using NetworkX.

In [9]:
```
# Step 1: Handle Missing Values
data.dropna(inplace=True)  # Drop rows with any missing values

# Step 2: Remove Duplicate Edges (Keep highest trust rating per transaction)
data.sort_values(by=["source", "target", "rating"], ascending=[True, True, False
data.drop_duplicates(subset=["source", "target"], keep="first", inplace=True)

# Step 3: Convert UNIX Timestamp to Datetime
```

```python
data["timestamp"] = pd.to_datetime(data["timestamp"], unit='s')

# Step 4: Check and Remove Self-Loops (Users rating themselves)
data = data[data["source"] != data["target"]]
display(data.sample(5))

# Create Directed Graph Using
G = nx.from_pandas_edgelist(data, source="source", target="target", edge_attr=["

# Step 7: Print Summary
print(f"Number of nodes: {G.number_of_nodes()}")
print(f"Number of edges: {G.number_of_edges()}")
print(f"Date Range: {data['timestamp'].min()} to {data['timestamp'].max()}")
```

	source	target	rating	timestamp
30037	3099	4833	3	2013-12-18 07:01:41.188260078
24537	4532	1018	3	2013-07-08 20:21:46.115129948
35065	5227	5945	1	2015-05-13 13:54:21.714519978
11443	2256	2127	1	2012-07-05 08:08:25.628230095
361	2	110	1	2011-02-16 17:45:31.025209904

```
Number of nodes: 5881
Number of edges: 35592
Date Range: 2010-11-08 18:45:11.728359938 to 2016-01-25 01:12:03.757280111
```

In [80]:

```python
G
```

Out[80]: `<networkx.classes.digraph.DiGraph at 0x1d6af9cdca0>`

Deep Research Questions Based on the Dataset

Research Question 1: What is the distribution of trust scores in the Bitcoin OTC network?

In [123…

```python
# Sort the dictionary by keys in ascending order
sorted_dict = dict(sorted(data["rating"].value_counts().items()))

# Display the keys and values in horizontal form
for key, value in sorted_dict.items():
    print(f"{key}: {value}", end="  ")
```

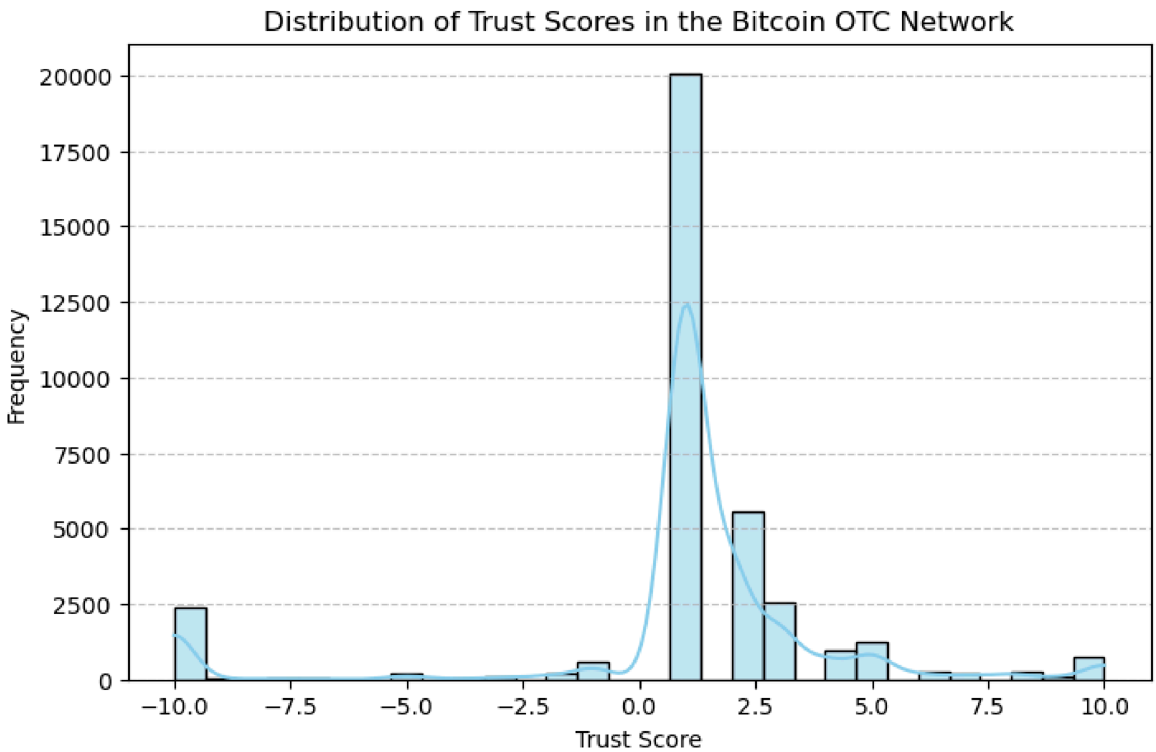
```
-10: 2413  -9: 20  -8: 31  -7: 14  -6: 5  -5: 179  -4: 27  -3: 91  -2: 182  -1: 6
01  1: 20048  2: 5562  3: 2561  4: 967  5: 1268  6: 265  7: 208  8: 277  9: 108
10: 765
```

```
Rating which also mean trust scores indicate *how much
confidence* user have in each
other during transactions, Therefore, understanding the
distribution of trust reveals
*if there are high-trust or low-trust or it is evenly spread*
```

In [10]:

```python
# Extract trust scores
trust_scores = data["rating"]
```

```
# Plot the distribution
plt.figure(figsize=(8, 5))

# Use Seaborn to plot a histogram with a KDE line
sns.histplot(trust_scores, bins=30, kde=True, color='skyblue', edgecolor='black'

# Add labels and title
plt.xlabel("Trust Score")
plt.ylabel("Frequency")
plt.title("Distribution of Trust Scores in the Bitcoin OTC Network")
plt.grid(axis='y', linestyle='--', alpha=0.7)

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



from the visuals, rating 1 appears the most, implying low mean trust, users are catious on who to trust.

In [35]:
```
# Compute basic statistics
mean_trust = trust_scores.mean()
median_trust = trust_scores.median()
variance_trust = trust_scores.var()

# Count negative trust scores
negative_trust_count = (trust_scores < 0).sum()

# Print results
print(f"Mean Trust Score: {mean_trust:.2f}")
print(f"Median Trust Score: {median_trust:.2f}")
print(f"Variance of Trust Scores: {variance_trust:.2f}")
print(f"Number of Negative Trust Scores: {negative_trust_count}")
```

```
Mean Trust Score: 1.01
Median Trust Score: 1.00
Variance of Trust Scores: 12.69
Number of Negative Trust Scores: 3563
```

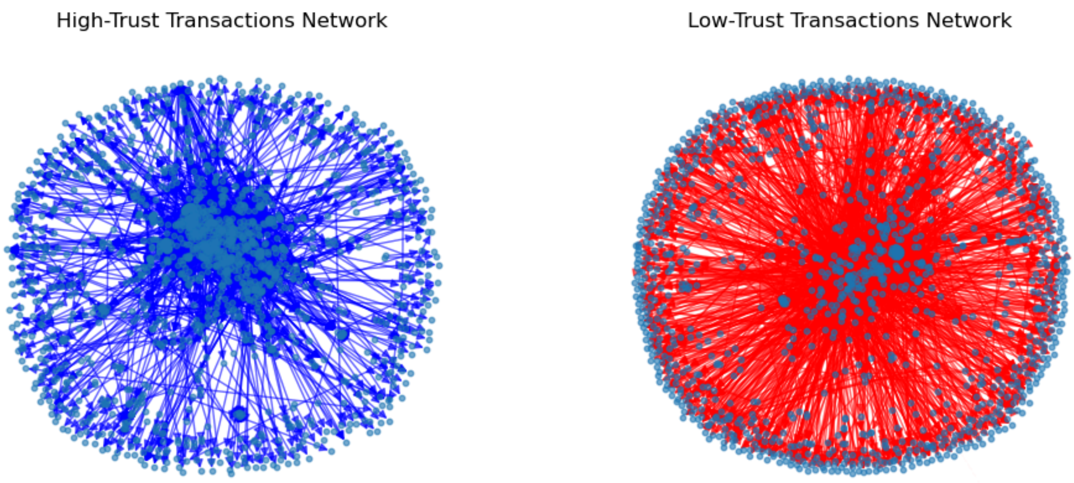
The distribution shows a network with a heavy concentration of neutral to slightly positive trust ratings. However, the variability and presence of a substantial number of negative ratings demonstrate that the network has a mix of cooperative and adversarial relationships, likely reflective of differing levels of user confidence and interaction quality.

In [ ]:

Research Question 2: How do high-trust and low-trust transactions differ in terms of network structure?

In [12]:

```python
# Define trust thresholds
high_trust_threshold = 5
low_trust_threshold = -5

# Filter high-trust and low-trust transactions
high_trust_data = data[data["rating"] >= high_trust_threshold]
low_trust_data = data[data["rating"] <= low_trust_threshold]

# Create separate graphs
G_high_trust = nx.from_pandas_edgelist(high_trust_data, source="source", target=
                                       create_using=nx.DiGraph())
G_low_trust = nx.from_pandas_edgelist(low_trust_data, source="source", target="t
                                      create_using=nx.DiGraph())

# Plot High-Trust Network
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
nx.draw(G_high_trust, node_size=10, edge_color="blue", alpha=0.6, with_labels=Fa
plt.title("High-Trust Transactions Network")

# Plot Low-Trust Network
plt.subplot(1, 2, 2)
nx.draw(G_low_trust, node_size=10, edge_color="red", alpha=0.6, with_labels=Fals
plt.title("Low-Trust Transactions Network")

plt.show()
```



✅ High-trust users tend to operate in well-connected, stable communities with repeat transactions.

✅ Low-trust transactions involve more scattered, unstructured interactions, possibly indicating uncertainty or one-time deals.

In [25]:
```
# Convert directed graphs to undirected graphs
G_high_trust_undirected = G_high_trust.to_undirected()
G_low_trust_undirected = G_low_trust.to_undirected()
```

In [43]:
```
import community.community_louvain as community_louvain

# Detect communities in the high-trust network (now undirected)
high_trust_partition = community_louvain.best_partition(G_high_trust_undirected)

# Detect communities in the low-trust network (now undirected)
low_trust_partition = community_louvain.best_partition(G_low_trust_undirected)

# Print the number of communities
print(f"Number of communities in High-Trust Network: {len(set(high_trust_partiti
print(f"Number of communities in Low-Trust Network: {len(set(low_trust_partition

# Visualize the communities in the High-Trust Network
#plt.figure(figsize=(8, 6))
#nx.draw(
   # G_high_trust_undirected,
    #node_color=[low_trust_partition[node] for node in G_low_trust_undirected.no
    #node_size=30,
    #cmap=plt.cm.jet,
    #with_labels=False
#)
#plt.title("Communities in High-Trust Network")
#plt.show()
```

```
Number of communities in High-Trust Network: 152
Number of communities in Low-Trust Network: 86
```

In [43]:
```
# Compute average degree
avg_degree_high = sum(dict(G_high_trust.degree()).values()) / len(G_high_trust.n
avg_degree_low = sum(dict(G_low_trust.degree()).values()) / len(G_low_trust.node

# Compute clustering coefficient
clustering_high = nx.average_clustering(G_high_trust)
clustering_low = nx.average_clustering(G_low_trust)

# Compute number of connected components
connected_components_high = nx.number_weakly_connected_components(G_high_trust)
connected_components_low = nx.number_weakly_connected_components(G_low_trust)

# Print results
print(f"High-Trust Transactions Network:")
print(f"  - Average Degree: {avg_degree_high:.2f}")
print(f"  - Average Clustering Coefficient: {clustering_high:.2f}")
print(f"  - Number of Connected Components: {connected_components_high}")

print(f"\nLow-Trust Transactions Network:")
print(f"  - Average Degree: {avg_degree_low:.2f}")
```

```
print(f"  - Average Clustering Coefficient: {clustering_low:.2f}")
print(f"  - Number of Connected Components: {connected_components_low}")
```

```
High-Trust Transactions Network:
  - Average Degree: 3.64
  - Average Clustering Coefficient: 0.06
  - Number of Connected Components: 132

Low-Trust Transactions Network:
  - Average Degree: 4.29
  - Average Clustering Coefficient: 0.01
  - Number of Connected Components: 72
```

✅ High-trust transactions form tight-knit, well-clustered communities where users interact within trusted circles.

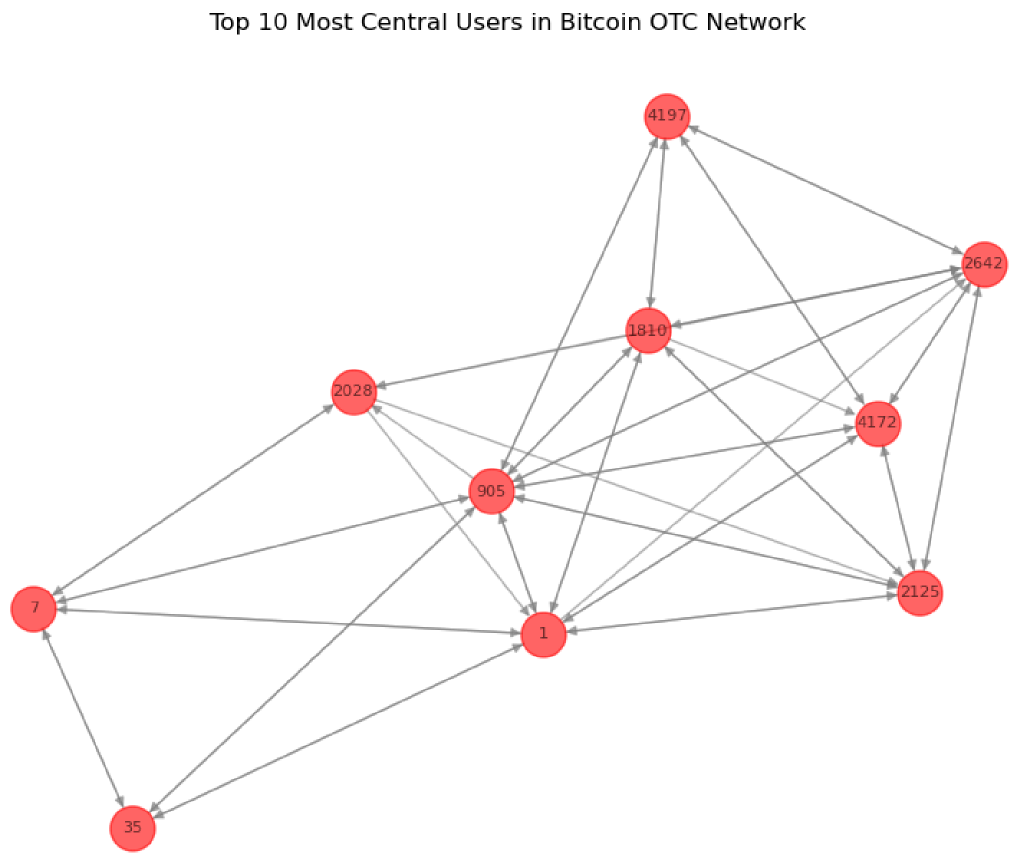
✅ Low-trust transactions show wider connectivity but weaker relationships, suggesting riskier, less structured transactions.

✅ The higher number of components in the high-trust network suggests that trust leads to fragmentation, whereas low-trust transactions remain more widespread and connected.

Research Question 3: What role do central users play in transaction reconciliation, and how does their influence change over time?

In [29]:

```
# Compute centrality metrics
degree_centrality = nx.degree_centrality(G)
betweenness_centrality = nx.betweenness_centrality(G)
pagerank = nx.pagerank(G)

# Get top 10 most central users
top_degree = sorted(degree_centrality.items(), key=lambda x: x[1], reverse=True)
top_betweenness = sorted(betweenness_centrality.items(), key=lambda x: x[1], rev
top_pagerank = sorted(pagerank.items(), key=lambda x: x[1], reverse=True)[:10]

# Extract node IDs for visualization
top_users = [user[0] for user in top_degree]

# Subgraph of central users
subgraph = G.subgraph(top_users)

# Visualize top central users
plt.figure(figsize=(8, 4))
nx.draw(subgraph, node_size=500, node_color="red", with_labels=True, font_size=8
plt.title("Top 10 Most Central Users in Bitcoin OTC Network")
plt.show()
```



Degree Centrality – Measures how many direct connections a node has.
Betweenness Centrality – Identifies nodes that act as bridges between different parts of the network.
Closeness Centrality – Determines how quickly a node can reach all others.
PageRank – Ranks nodes based on their importance in spreading information.

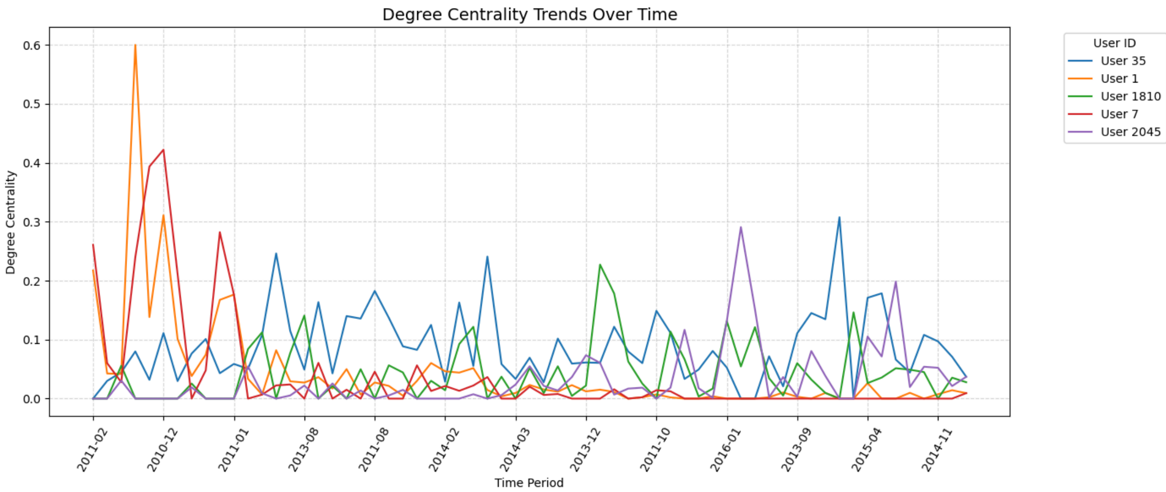
In [31]:

```
# Define time periods (e.g., group by month)
data["year_month"] = data["timestamp"].dt.to_period("M")

# Compute degree centrality for each time period
time_centrality = {}

for period in data["year_month"].unique():
    sub_data = data[data["year_month"] == period]
    G_sub = nx.from_pandas_edgelist(sub_data, source="source", target="target",
    degree_centrality_sub = nx.degree_centrality(G_sub)
    time_centrality[period] = degree_centrality_sub

# Convert to DataFrame for analysis
centrality_df = pd.DataFrame(time_centrality).T.fillna(0)

# Display top users' influence over time
#centrality_df.head(10)  # Shows centrality values for top users across time
```

In [37]:

```
# Plot the line graph
plt.figure(figsize=(14, 6))
```

```python
# Select top N users with the highest average centrality over time
top_users = centrality_df.mean().sort_values(ascending=False).head(5).index

for user in top_users:
    plt.plot(centrality_df.index.astype(str), centrality_df[user], label=f"User

# Formatting
plt.title("Degree Centrality Trends Over Time", fontsize=14)
plt.xlabel("Time Period")
plt.ylabel("Degree Centrality")

# Optimize xticks (reduce clutter)
xtick_positions = np.arange(0, len(centrality_df.index), step=5)  # Show every 5
plt.xticks(xtick_positions, centrality_df.index[xtick_positions].astype(str), rc

plt.legend(title="User ID", bbox_to_anchor=(1.05, 1), loc="upper left")  # Move
plt.grid(True, linestyle="--", alpha=0.5)
plt.tight_layout()  # Adjust layout to fit x-labels
plt.show()
```



The graph illustrates degree centrality trends over time for selected users in the Bitcoin OTC network. Degree centrality measures how connected a user is within the network, reflecting their role in transaction reconciliation.

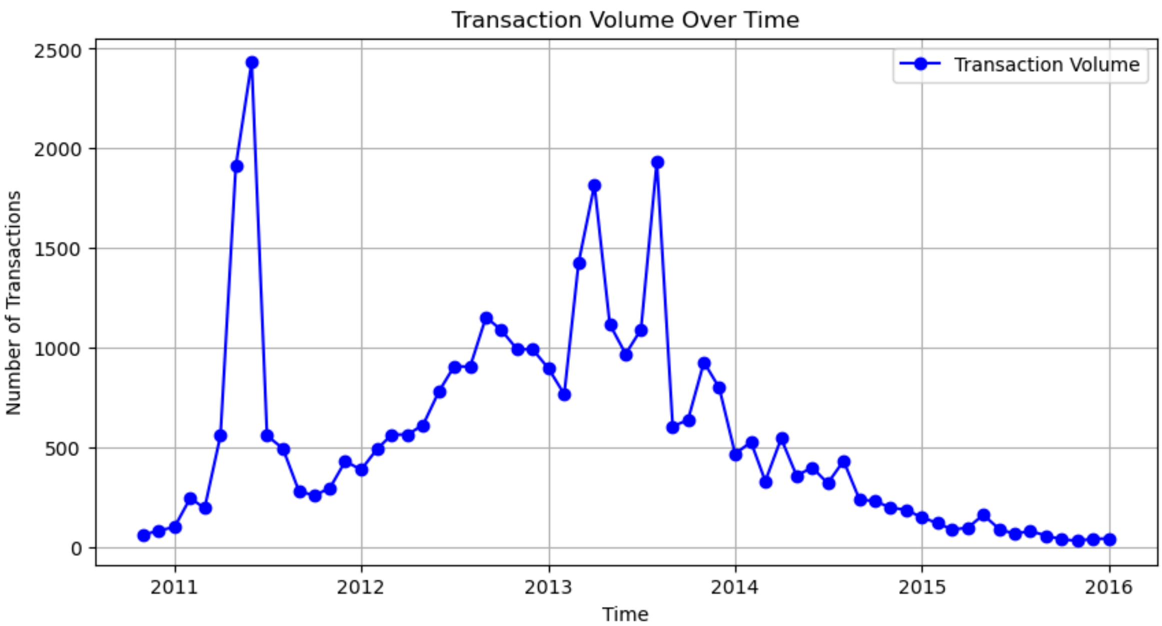
```
== Some users (e.g., User 1 and User 7) exhibited early spikes
in centrality, suggesting that they were highly active in
facilitating transactions during specific periods but later
declined in influence.
== Other users (e.g., User 35 and User 2045) maintained sporadic
or moderate centrality, indicating sustained but fluctuating
participation in the network.
== The overall declining trend in centrality suggests that no
single user retained dominance over time, possibly due to shifts
in trust or the entry of new participants in the network.
```

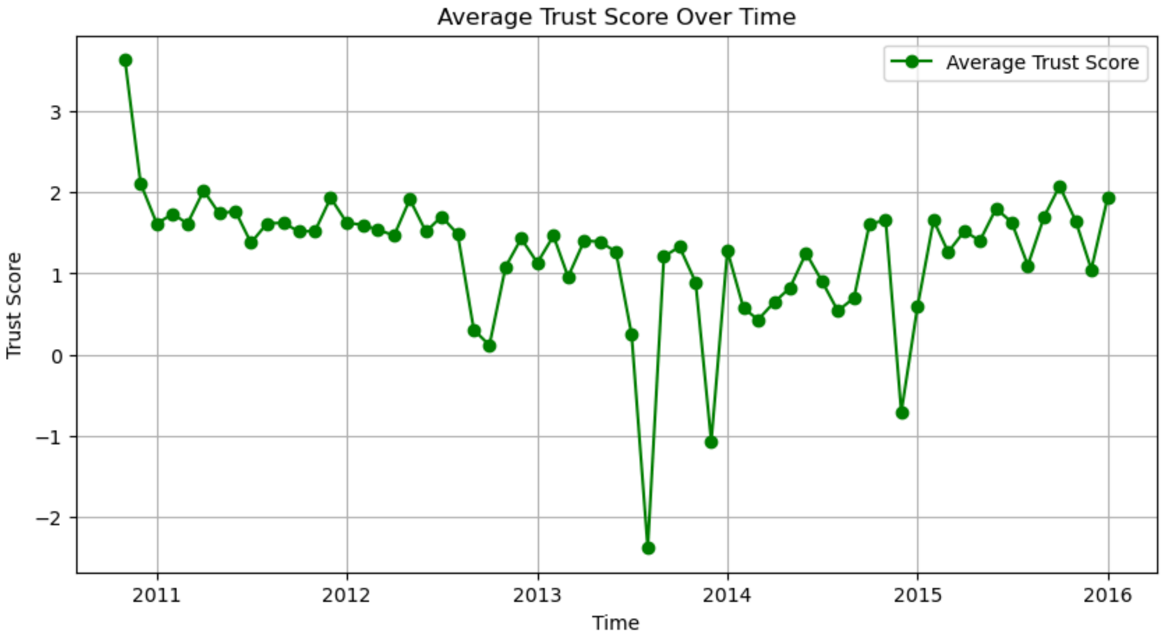
In [ ]:

Research Question 4: How does transaction volume and trust score evolve over time?

In [51]:
```python
import matplotlib.pyplot as plt
import pandas as pd
```

```
# Ensure timestamps are in datetime format
data["timestamp"] = pd.to_datetime(data["timestamp"], unit="s")

# Group by month and compute transaction volume & average trust score
data["year_month"] = data["timestamp"].dt.to_period("M")
transaction_trends = data.groupby("year_month").agg({"rating": ["count", "mean"]
transaction_trends.columns = ["Transaction Volume", "Average Trust Score"]

# Convert period index to datetime for plotting
transaction_trends.index = transaction_trends.index.to_timestamp()

# Plot transaction volume over time
plt.figure(figsize=(10, 5))
plt.plot(transaction_trends.index, transaction_trends["Transaction Volume"], mar
plt.xlabel("Time")
plt.ylabel("Number of Transactions")
plt.title("Transaction Volume Over Time")
plt.grid(True)
plt.legend()
plt.show()

# Plot average trust score over time
plt.figure(figsize=(10, 5))
plt.plot(transaction_trends.index, transaction_trends["Average Trust Score"], ma
plt.xlabel("Time")
plt.ylabel("Trust Score")
plt.title("Average Trust Score Over Time")
plt.grid(True)
plt.legend()
plt.show()
```






```
Transaction Volume Over Time (Top Graph)

    The number of transactions fluctuates significantly over
time, with notable peaks around 2011-2013.
    There is a sharp increase in transaction volume in 2011,
reaching a peak close to 2500 transactions.
    After 2013, the volume shows a general declining trend, with
periodic spikes. By 2015-2016, the transaction activity
diminishes significantly.

Average Trust Score Over Time (Bottom Graph)

The trust score starts high (~3.5) but declines over time,
showing volatility.
There are multiple drops in trust scores, particularly in 2013
and 2014, where negative values are observed.
Trust scores recover slightly after 2014 but remain unstable.
```

In [53]:

```
# Compute percentage change in transaction volume & trust score
transaction_trends["Transaction Volume Change (%)"] = transaction_trends["Transa
transaction_trends["Trust Score Change (%)"] = transaction_trends["Average Trust

# Display key statistics
transaction_trends.head(10)  # Show first 10 time periods
```

Out[53]:

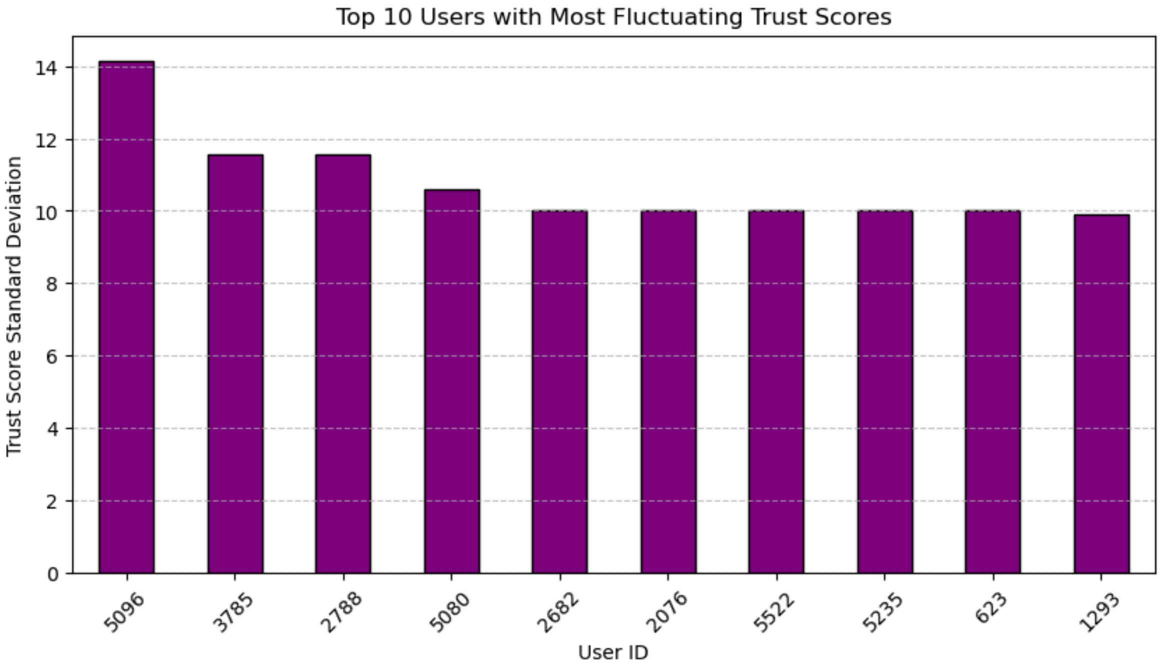
year_month	Transaction Volume	Average Trust Score	Transaction Volume Change (%)	Trust Score Change (%)
2010-11-01	60	3.633333	NaN	NaN
2010-12-01	82	2.109756	36.666667	-41.933318
2011-01-01	99	1.616162	20.731707	-23.395808
2011-02-01	245	1.734694	147.474747	7.334184
2011-03-01	194	1.613402	-20.816327	-6.992116
2011-04-01	559	2.021467	188.144330	25.292198
2011-05-01	1911	1.739403	241.860465	-13.953404
2011-06-01	2433	1.768598	27.315542	1.678448
2011-07-01	558	1.378136	-77.065351	-22.077495
2011-08-01	494	1.617409	-11.469534	17.362051

In [ ]:

Research Question 5: Do some users frequently engage in inconsistent or fluctuating trust ratings?

In [55]:

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

# Compute trust score standard deviation per user
user_trust_variability = data.groupby("source")["rating"].std().dropna()

# Identify top 10 users with the highest trust variability
top_fluctuating_users = user_trust_variability.sort_values(ascending=False).head

# Plot variability in trust ratings for top fluctuating users
plt.figure(figsize=(10, 5))
top_fluctuating_users.plot(kind="bar", color="purple", edgecolor="black")
plt.xlabel("User ID")
plt.ylabel("Trust Score Standard Deviation")
plt.title("Top 10 Users with Most Fluctuating Trust Scores")
plt.xticks(rotation=45)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```



In [ ]:

In [57]:
```
# Compute trust variability statistics
mean_variability = user_trust_variability.mean()
high_variability_users = (user_trust_variability > mean_variability * 2).sum()

# Print results
print(f"Average Trust Score Variability: {mean_variability:.2f}")
print(f"Number of High Variability Users: {high_variability_users}")
```

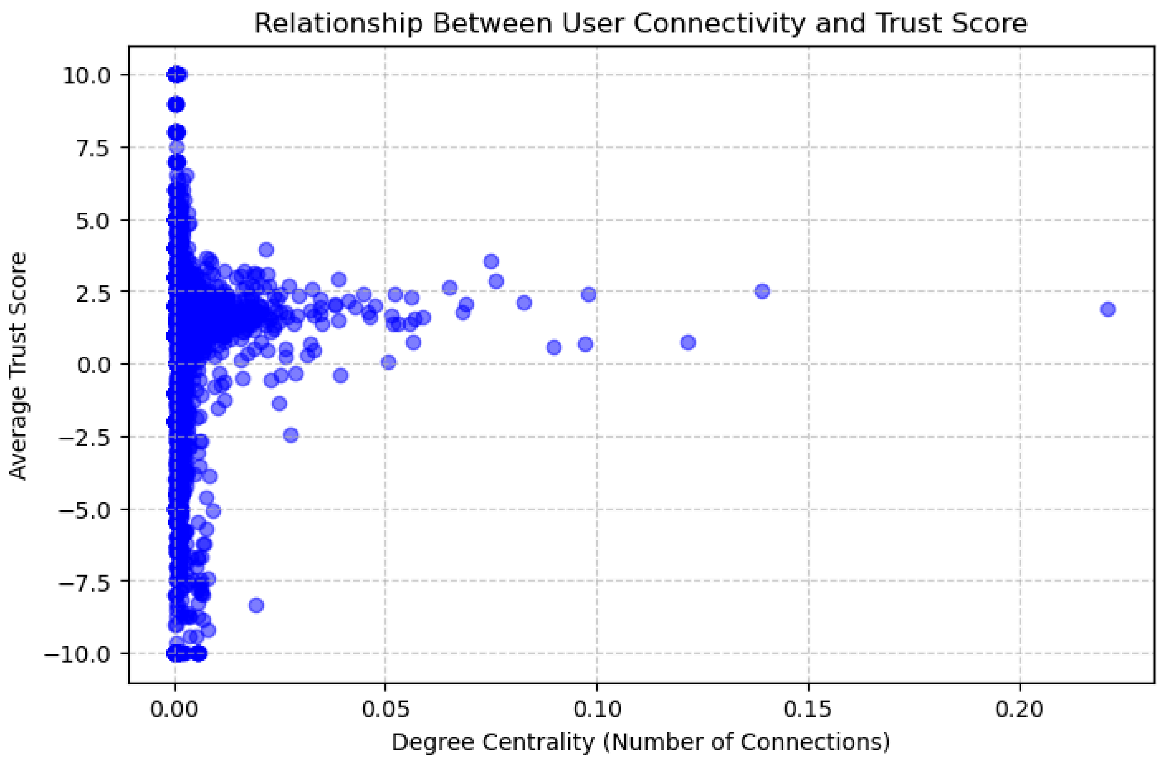
```
Average Trust Score Variability: 1.75
Number of High Variability Users: 546
```

In [ ]:

Research Question 6: Are transactions with lower trust scores more likely to involve users with fewer connections?

In [59]:
```
import matplotlib.pyplot as plt
import pandas as pd
import networkx as nx

# Compute degree centrality (number of connections per user)
degree_centrality = nx.degree_centrality(G)

# Compute average received trust score per user
user_avg_trust = data.groupby("target")["rating"].mean()

# Merge centrality and trust score data
user_analysis = pd.DataFrame({"degree_centrality": degree_centrality, "avg_trust

# Scatter plot: User Connections vs. Trust Score
plt.figure(figsize=(8, 5))
plt.scatter(user_analysis["degree_centrality"], user_analysis["avg_trust_score"]
plt.xlabel("Degree Centrality (Number of Connections)")
plt.ylabel("Average Trust Score")
plt.title("Relationship Between User Connectivity and Trust Score")
```

```
plt.grid(True, linestyle="--", alpha=0.6)
plt.show()
```



In [61]:
```
# Compute correlation between degree centrality and trust score
correlation = user_analysis["degree_centrality"].corr(user_analysis["avg_trust_s

# Print results
print(f"Correlation between Degree Centrality and Trust Score: {correlation:.2f}
```

```
Correlation between Degree Centrality and Trust Score: 0.04
```

Given the broad scatter of points, degree centrality alone is not a strong predictor of a user’s trust score.
Other factors—such as transaction history, reputation, or external events—likely play a significant role in determining how trusted or distrusted a user becomes.

In summary, while higher connectivity might offer some advantages in establishing trust, the plot shows that trust levels vary greatly even for users with similar connectivity, leading to a weak or negligible overall correlation.

In [ ]: