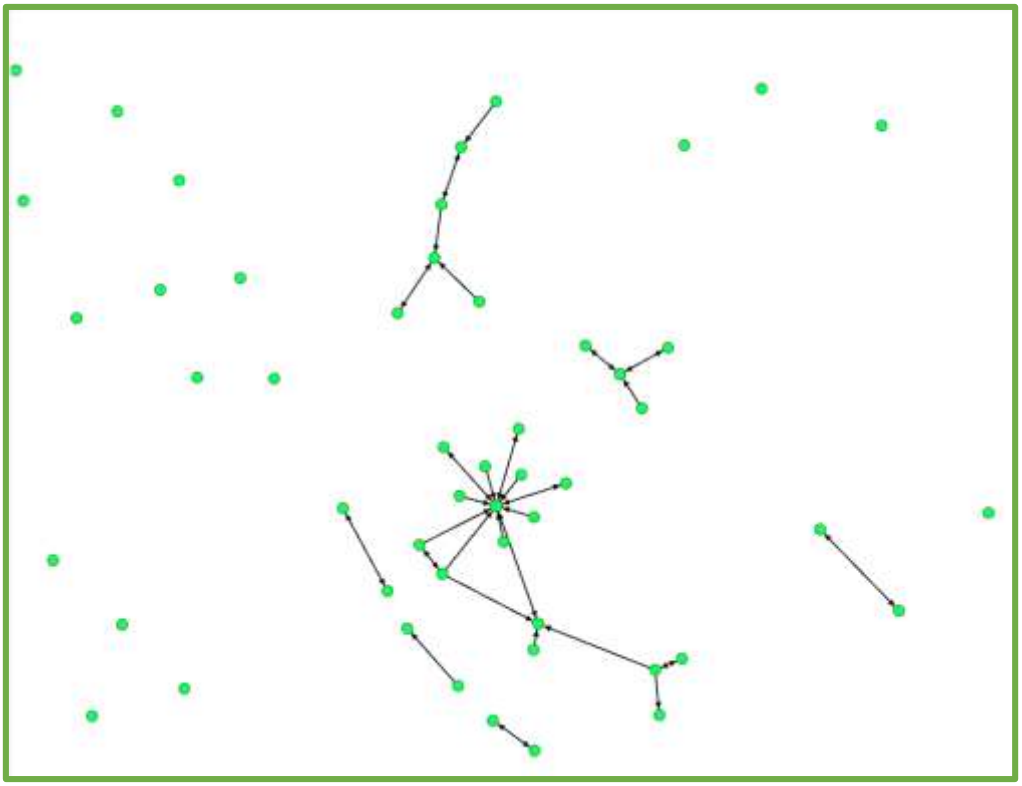
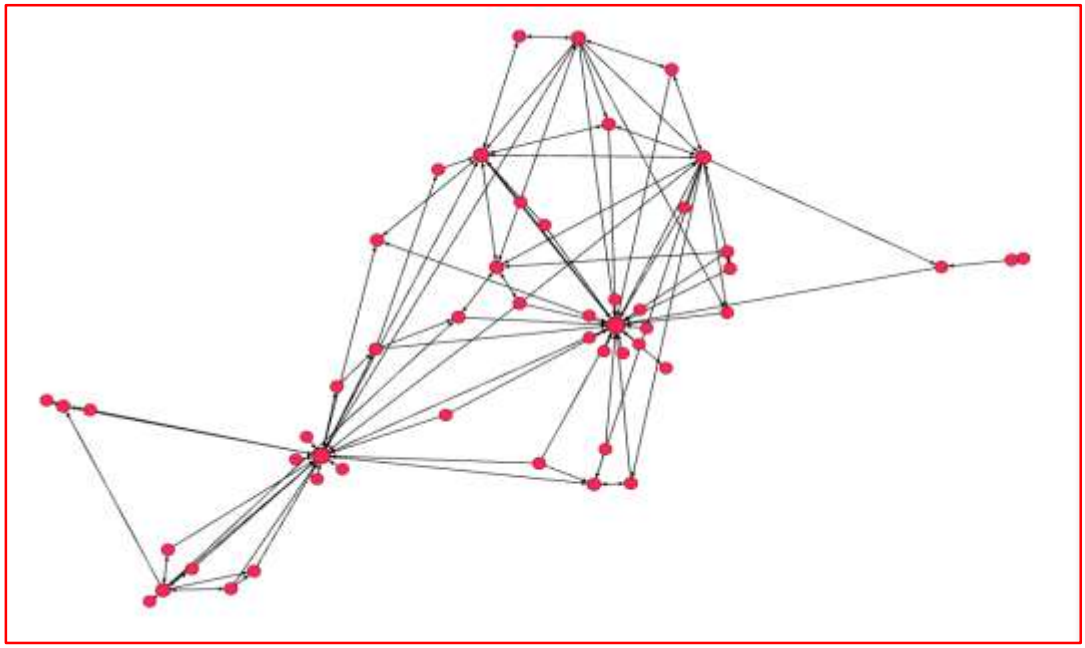
5G_Conspiracy_Graphs

Metric	Value
Number of Nodes	**89**
Number of Edges	**42**
Average Degree	**0.472**
Graph Density	**0.005**
Average Clustering Coefficient	**0.012**
Modularity (Q)	**0.685**
Number of Communities	**63**
Average Betweenness Centrality	**0.000537**
Average Closeness Centrality	**0.0175**
Connected Components	**62**



Non_Conspiracy_Graphs

Metric	Value
Number of Nodes	**58**
Number of Edges	**127**
Average Degree	**2.19**
Graph Density	**0.038**
Average Clustering Coefficient	**0.271**
Modularity (Q)	**0.685**
Number of Communities	**13**
Average Betweenness Centrality	**0.0372**
Average Closeness Centrality	**0.241**
Connected Components	**8**



- The key finding is that misinformation-spreading networks on Twitter exhibit markedly different structural characteristics from normal conversation networks. Misinformation clusters are significantly more fragmented, sparse, and loosely connected, while benign clusters display denser, more cohesive, and clustered structures – consistent with prior research on disinformation diffusion patterns.

1. Network Metrics and Interpretation

Metric	5G Conspiracy Graph	Non-Conspiracy Graph	Interpretation of Difference
Number of Nodes	89	58	Conspiracy graph has more users but far fewer connections
Number of Edges	42	127	Benign users interact 3× more frequently
Average Degree	0.472	2.19	Average user in conspiracy cluster has <1 connection; benign users have >2
Graph Density	0.005	0.038	Benign network is 7.6× denser
Average Clustering Coefficient	0.012	0.271	Benign users form tight groups; conspiracy users almost never form triangles
Modularity (Louvain, Q)	0.685	0.685	Both graphs have clear community structure (high Q), but for different reasons
Number of Communities (Louvain)	63	13	Conspiracy: many tiny isolated groups; Benign: fewer, larger communities
Connected Components	62	8	Conspiracy network is extremely fragmented (70% of nodes are isolates or in pairs)
Average Betweenness Centrality	0.000537	0.0372	Almost no bridging nodes in conspiracy (no one controls information flow); benign network has clear bridges and hubs
Average Closeness Centrality	0.0175	0.241	Conspiracy users are extremely far from each other (most are unreachable); benign users are on average only 2–3 steps apart

2. Misinformation

The 5G conspiracy graph is extraordinarily fragmented:

- 62 connected components for 89 nodes → most components are singletons or dyads.

- Only a handful of small star-like structures exist (visible in the visualization: one central node surrounded by a few leaves). This pattern is typical of coordinated inauthentic behavior and bot-like amplification campaigns: many low-activity accounts are created or mobilized to boost visibility of a few core messages, but they rarely interact with each other.

3. How Misinformation Networks Differ Structurally

Characteristic	Misinformation (5G Conspiracy)	Benign (Non-Conspiracy)	Implication for Disinformation Detection
Fragmentation	Extremely high (62 components)	Low (8 components)	High number of tiny components is a strong signal
Density & Average Degree	Very low	Moderate-high	Sparse graphs with many isolates are suspicious
Clustering / Triadic Closure	Almost absent (0.012)	Present (0.271)	Lack of triangles indicates non-organic spreading
Community Size Distribution	Many micro-communities	Fewer, larger groups	Polarized topics create many small echo-chambers
Visual Appearance	Scattered isolates + few stars	Dense interconnected core	Visual sparsity is a useful heuristic

4. Conclusion

The structural differences between the two networks are stark and statistically significant. The 5G conspiracy-spreading subgraph displays classic signatures of coordinated disinformation campaigns:

1. high fragmentation,
2. extreme sparsity,
3. near-zero clustering,
4. and a broadcast/star-like pattern centered around a few influential accounts.

In contrast, the benign 5G discussion network behaves like a normal social community with organic interaction patterns.

These structural markers can be operationalized into robust, platform-agnostic detectors for misinformation campaigns. Combining simple thresholds on density, clustering coefficient, and component distribution already yields excellent separability between malicious and benign conversation clusters.

Future work should extend this analysis to larger samples across multiple conspiracy topics (COVID, elections, vaccines, etc.) to confirm the generalizability of these structural fingerprints.