COMPETITIVE ADAPTATION IN TERRORIST NETWORKS: DIFFERENCES BETWEEN THE AL-MUHAJIROUN AND THE IRISH REPUBLICAN ARMY

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14. ABSTRACT
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Abstract

Competitive adaptation refers to how adversaries such as terrorist groups and government counterterrorism agencies learn and adapt behavior based on behavior of the other. Using significant events as guides, studying the adaptation will identify and characterize how groups will evolve.

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1 Introduction

Competitive adaptation in terrorist networks (CATNET) is a multi-disciplinary research project concerned with modeling the social, psychological and cultural characteristics of adaptive militant networks. In this paper, we explore the differences in adaptation between the Al-Muhajiroun (AM) and the Irish Republican Army (IRA) terrorist groups. We use the text analysis software, AutoMap [1], to extract meta-networks of entities from a variety of text sources that address the AM and IRA (i.e., CATNET data). We then use the network analysis software, ORA [3], to perform analyses on the structure of meta-networks formed from the various text sources.

The Al-Muhajiroun (AM) is a banned Islamist terrorist organization which was based in Britain and has been linked to international terrorism, homophobia and anti-Semitism. Al-Muhajiroun's main aim is to spread public awareness about Islam and its ideologies, to influence public opinion in favor of Sharia law and to prove to the people that Islam is a viable ideological and political initiative. It aims to unite all the Muslim people on a global scale.

Omar Bakri Muhammad and Anjem Choudry are known to have led the AM, which was founded in 1983 by Omar Bakri Muhammad in Mecca, Saudi Arabia. The AM operated in the United Kingdom from 14 January 1986 until the British Government announced an intended ban in August 2005. The group was then re launched in June 2009. One of the major attacks by this group includes the bombing of a café in Tel Aviv, Israel. This attack killed three people and wounded 60 others. The AM became notorious for its conference "The Magnificent 19", praising the September 11, 2001 attacks.

The Irish Republican Army (IRA) was an Irish republican revolutionary military organization, evolved from the Irish Republican Brotherhood. The Irish Republican Brotherhood originated in 1913, and staged the Easter Rising in 1916. In 1919, the Irish Republic that had been proclaimed during the Easter Rising was established by an elected assembly, and the IRA was recognized as its legitimate army. Thereafter, the IRA waged a guerilla campaign against British rule in Ireland during 1919-21 – the Irish War of Independence. After the Anglo-Irish Treaty was signed in 1921, which ended the War of Independence, the IRA split into two groups. Members who supported the treaty formed the nucleus of the Irish National Army founded by IRA leader Michael Collins. However, much of the IRA was opposed to the treaty. The anti-treaty IRA fought a civil war with their former comrades in 1922–23, with the intention of creating a fully independent all-Ireland republic. Having lost the civil war, this group remained in existence and called itself the IRA, with the intention of overthrowing both the Irish Free State and Northern Ireland and achieving the Irish Republic proclaimed in 1916.

In the following, we describe our approach for meta-network extraction and analyses. Results of the analyses are then presented and discussed. We conclude by discussing observed differences between the AM and IRA as adaptive organizations.

2 Approach

We used the Data-to-Model (D2M) script [4] in AutoMap [1] to extract meta-networks from each of the text sources for the AM and IRA. Meta-network analyses and visualizations were performed using ORA.

2.1 Text Sources

Primary and secondary data sources were used to explore competitive adaptation in terrorist networks. The study used interview material, public statements, and open source news reports to compare what a group or individual has said in private, said in public, and what was said about them. The primary source material stems from first hand interviews with terrorists, and the secondary source material from news reports.

The data for the AM were obtained from five different sources, these include:

1. **AMcourt** – The AM court texts contain articles pertaining to the court cases held at the Superior court of justice against Mohammad Momin Khawaja (7 texts).

2. **AMinterviews** – AM interviews contain text data pertaining to the interviews that took place and discussed the Al-Muhajiroun group specifically, this source contains two different types of interview texts. One was based on interviews with the public and the other was based on interviews with AM members (99 texts).

3. **AMnews** – The AM news source contains all the relevant news articles and publication in the news on the Al-Muhajiroun group published mostly in London, USA and Australia (approximately 15,000 texts).

4. **AMpress** – The AM press source contains the press releases relating to the Al-Muhajiroun group (approximately 300 texts).

5. **AMchoudry** – The AM choudry data contains the original text notes of an interview with Anjem Choudary, and three of his young acolytes held on September 22, 2007 in South London (2 texts).

The data for the IRA were obtained from two sources:

1. **IRAcourt** – The IRA court data contains the relevant text data pertaining to the court cases on the IRA obtained mostly from Lexis Nexis (537 texts).

2. **IRAinterviews** – The IRA interviews source contains the relevant text data pertaining to the interviews that took place and discussed the IRA group specifically. It consists of two types of interview texts; one from public and the other from interviews conducted with the members of the IRA group (18 texts).

2.2 Meta-network Analyses

We applied the standard D2M script in AutoMap to each data source identified above to generate a set of seven source-specific meta-networks. Each meta-network represents the co-occurrence of standard DNA entities (e.g., agents, organizations, tasks, resources, locations, etc.) provided by source texts as a system of networks. The meta-network for a source thus provides a unified model of the associations (i.e., co-occurrence) among entities which were described by all texts available in CATNET for that source.

In line with Network Text Analysis (NTA) techniques, we compared and contrasted the meta-network structures for each data source. As is typical during NTA, we performed a variety of analyses at the node-, network-, and meta-network levels of analysis. These typical NTA analyses were designed to determine which concepts were most important in the aggregate narratives represented by the meta-networks extracted, the complexity and coherence of the narratives, and whether the different text sources emphasized different concepts or themes.

The new aspect of the NTA reported below is related to how we examined adaptation for the AM and IRA. A traditional NTA approach for examining adaptation would require dividing each text source into a time-series of meta-networks, and then analyzing how the structure of these aggregate narratives changes over time. Given the CATNET data, this approach would have required possibly contentious assumptions about the temporal periods covered by each text. Furthermore, the CATNET text sources vary widely in the number of samples available, which would have caused problems when trying to define time periods that are consistent across all sources.

Rather than looking for structural evidence of adaptation in the two terrorist groups, we took a more semantically oriented (cf. content oriented) approach. We categorized terms found in the text data into three general keywords representing different types of adaptation. These three keywords are Learning, Education and the general term, Adaptation. The terms which were grouped into the keyword Adaptation were terms like adjust, alter, amend and accustom. The terms such as heard, idea, figured out were grouped into the keyword Learning. Similarly, terms like study, teach, educate were merged into the keyword Education. Subsequently, we recoded (i.e., merged) all relevant nodes in the meta-networks extracted from the text sources into nodes representing one of the three keywords, and performed structural NTA on the resultant meta-networks.

3 Narrative Structures

The following provides structural comparisons of the AM and IRA narratives – and of the different text sources for each terrorist group – at the node-, network-, and meta-network levels of analysis.

3.1 Concept Counts

Node-count analyses (cf. content analysis) indicate the importance of concepts addressed in the different text sources. Our examination of conceptual importance is further refined by looking at the number of concepts that are classified as different types of entities in the standard DNA ontology. Table 1 below provides node counts for the different classes of entities extracted from all AM text sources. Agents are further classified as being specific or generic, depending on whether they have one or more referents, respectively.

Node type	Anjem Choudry	Interviews	News Articles	Press Releases	Court Cases	Union
Generic Agent	187	1555	4224	870	470	5505
Specific Agent	34	146	384	96	84	573
Organization	83	403	1412	271	176	1818
Belief	6	17	24	14	1	36
Event	33	148	230	88	72	329
Location	111	671	1682	517	295	2209
Task	253	1129	1446	751	561	2029
Time	21	54	638	155	180	932
Resource	184	1707	2920	1016	682	4215
Knowledge	280	1483	2507	1090	688	3651

Table 1: Number of nodes- Total and per node type for each of the sources (Al-Muhajiroun)

From the Table 1, we see that the majority of the concepts for each of the node classes are from the News articles on AM group (AM news). The network generated by the union for all the sources for the AM group has majority of concepts which are classified as the generic agents (25.8% of the total nodes) – indicating that AM texts tend to speak in generalities when referring to people.

Node Type	Court Cases	Interviews	Union
Generic Agent	**8424**	**449**	**8524**
Specific Agent	**630**	**25**	**643**
Organization	**3583**	**191**	**3653**
Belief	**10**	**1**	**10**
Event	**413**	**61**	**426**
Location	**3122**	**351**	**3203**
Task	**2754**	**925**	**2886**
Time	**4055**	**114**	**4115**
Resource	**4385**	**756**	**4608**
Knowledge	**5890**	**746**	**6032**

Table 2: Number of nodes- Total and per node type for each of the sources (IRA)

From Table 2, we infer that the majority of the concepts are from the texts obtained from the court cases. This shows that the texts from the court trials are dominant (in numbers) over the texts from the interviews with regard to the IRA group. Similar to the AM narratives, IRA narratives tend to speak in generalities when referring to people.

Comparing the two groups (AM and IRA), we see that the IRA narratives contain more concepts (~34,000) than the AM narratives (~21,000), which indicates that the IRA text sources are more conceptually diverse than the AM text sources – even though the CATNET data set provides a larger variety of text sources for the AM than for the IRA.

3.2 Conceptual Coherence

The complexity of a meta-network is defined as the density of the network created when all node classes are collapsed into a single node class. In NTA, complexity (and density) measure global conceptual coherence in terms of the inter-relatedness of associations among all concepts in aggregate narratives.

Performance Measure	Anjem Choudry	Interviews	News Articles	Press Articles	Court Cases	Union
Overall Complexity	0.024	0.006	0.003	0.008	0.012	0.003

Table 3: Meta-network complexity for each AM text source

From Table 3 above, we observe that the source AM choudry gives us a meta-network which is the most complex or coherent. This means that the concepts or the nodes are more closely connected and related to each other as compared to the other sources. The complexity of the meta-network obtained from the AM choudry texts is quite high since this source comprises of the interviews and opinions of a single person, he has only a one-sided opinion and view. Or more generally, the concepts conveyed by one person tend to be more inter-related than the concepts conveyed by multiple people that contributed to the other text sources.

From Table 3 above, we see that the complexity of the meta-network generated from the source AM news is the least coherent of the text sources. This is because we have news articles from various publications that have varied opinions and views of different journalists on the terrorist group.

However, it is generally known that the complexity (cf. density) of meta-network is inversely related to the size of the meta-network. This could be the explanation for why the complexity of the AM choudry (only 2 articles) source is eight times that of the AM news source (consists of around 14,000 articles).

Performance Measure	Court Cases	Interviews	Unions
Overall			
Complexity	0.002	0.008	0.002

Table 4: Meta-network complexity for each of the IRA text sources

From the Table 4, we observe that the coherence of the meta-network from the IRA interviews source is four times higher than texts from our IRA court.

The inverse dependency of complexity with the size of meta-network is seen for the IRA data also; the IRA interview texts contain only 18 articles as compared to 500 articles from the IRA court texts.

Upon closer inspection of the complexity of the IRA court narrative as compared to the AM court narrative, we see that the concepts found in texts describing the Al-Muhajiroun are six times more coherent (i.e., more highly associated) than those in texts describing the Irish Republican Army. Secondly, we see that the overall meta-network (i.e., union of all text data sources) for the AM is more coherent as compared to the IRA (i.e., union), though only by a small margin. Thus, while the IRA narrative is more conceptually diverse, the AM narrative is more conceptually coherent.

In addition to examining the global coherence of narratives for all entity (i.e., node) types, we can also examine the global coherence of narratives with respect to particular entities. In Table 5, we show the density (i.e., the ratio of observed ties between nodes to possible ties between nodes) for each of the member networks for the meta-networks extracted from each text source (for the AM). We restricted this analysis to specific agents (i.e., omitted generic agents).

Network type	Anjem Choudry	Interviews	News Articles	Press Articles	Court Cases	Union
Agent x agent specific	0.020	0.014	0.008	0.019	0.075	0.006
Agent x Organization	0.023	0.011	0.005	0.012	0.030	0.004
Agent x Belief	0.083	0.046	0.020	0.046	0.607	0.016
Agent x Event	0.014	0.006	0.005	0.007	0.021	0.004
Agent x Location	0.027	0.011	0.006	0.013	0.037	0.005
Agent x Task	0.022	0.010	0.010	0.014	0.032	0.007
Agent x Time	0.015	0.004	0.002	0.005	0.012	0.001
Agent x Resource	0.011	0.003	0.003	0.005	0.018	0.002
Agent x Knowledge	0.028	0.009	0.006	0.013	0.029	0.004

Table 5: Density of networks for each of the source of AM Group

Looking at the density metrics for AM court texts, we see that the agent-by-agent and the agent-by-organization networks are the most coherent as compared to the networks obtained from any other source for the Al-Muhajiroun group. (The relatively high density of agent-by-belief networks can be considered an artifact of very small network sizes.)

Comparing the two sources of data for the IRA group (see Table 6), we see that the texts from interviews seem to generate almost twice as more coherent networks as compared to the court cases when each node class is taken into close consideration.

Network type	Court Cases	Interviews	Union
Agent x agent specific	0.006	0.01	0.006
Agent x Organization	0.003	0.008	0.003
Agent x Belief	0.002	0.0	0.002
Agent x Event	0.004	0.007	0.003
Agent x Location	0.004	0.01	0.004
Agent x Task	0.008	0.007	0.008
Agent x Time	0.002	0.003	0.002
Agent x Resource	0.004	0.004	0.003
Agent x Knowledge	0.005	0.01	0.004

Table 6: Density of networks for each of the source of IRA Group

Comparing the two terrorist groups on the basis of the density of the network from various sources taking into consideration all the node classes, the first general observation is that the texts collected from the court cases generate the most coherent networks for AM whereas they generate the least coherent networks for IRA. This may well be an artifact of different sample sizes. The AM court data consists of only 7 texts, fewer samples than all other AM text sources except the Choudry interviews (2 texts). In contrast, the IRA court source consists of 537 texts, providing a substantially larger sample than the 18 IRA interview texts.

A second general observation is that the texts collected from the interview sources for the two groups tend to be more coherent in the case of AM as compared to IRA when examined on a network-by-network level. This trend is the reverse of what would be expected as an artifact of different sample sizes (99 AM versus 18 IRA interviews). What makes this finding more interesting is that the AM interviews include group members and nonmembers, which could be expected to decrease coherence. Moreover, this difference in the global coherence of AM and IRA interviews was not apparent when examining meta-network complexity (i.e., global coherence without consideration of entity type).

3.3 Specific Agents

In the following we restrict our attention to networks of specific agents extracted from the narratives. We did this for each terrorist group (AM and IRA). The network level statistics which we discuss include the clustering coefficient, density, number of isolates, closeness centrality and degree centrality.

Network measure	**Interviews**	**Union**
Density	0.014	0.006
Clustering coefficient	0.17	0.209
Number of Agents	146	573
Number of isolates	74	270
Link count	148	1018
Reciprocity	1.0	1.0
Characteristic path length	2.766	3.056
Network fragmentation	0.797	0.742
Krackhardt connectedness	0.203	0.258
Krackhardt efficiency	0.962	0.983
Krackhardt hierarchy	0.0	0.0
Krackhardt upperboundedness	1.0	1.0
Degree centralization	0.175	0.06
Betweenness centralization	0.087	0.052

Closeness centralization	0.006	0.001
Eigenvector centralization	0.462	0.448

Table 7: Network level measures for Al-Muhajiroun Group

Table 7 above shows the metrics for various network level measures for the Al-Muhajiroun (AM), considering only the specific agents. As before, the problematic network density metric indicates that the narrative from interviews is more globally coherent than the overall (union) narrative. Given how the difference in network sizes can influence density, we examined mean closeness centrality and mean degree centrality as alternative metrics of global coherence. Mean closeness centrality of the network obtained from the interview texts is six times that of the network created from the union of texts. Since the closeness centrality is a measure of nearness of the ego node to the neighboring nodes, it shows that the interviews source creates a network with overall closer links in comparison to the network from all other sources. Degree centrality is a measure of number of other nodes that one node is directly connected to. From Table 7, we see that the AM interviews creates a network whose degree centrality is three times as that of all other sources, which implies that the interviews source gives us information about a network in which agents which are highly active or a network in which each agent is known by a lot of other agents. Taken together, mean closeness- and mean degree centrality indicate that the interview narrative is more globally coherent than the overall narrative.

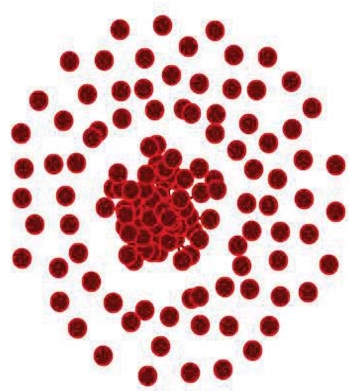

Figure 1: Agent-by-agent network formed by the texts from the AM interviews.

However, when we visualize the agent x agent network from interviews (see Figure 1 above), we see that the narrative describes a core group of inter-related agents surrounded by a large number of isolated agents. Indeed, 50% of the agents extracted from the interview narrative are not associated with other agents. In contrast, a visualization of the agent x agent network formed from all sources indicates that considering all sources together may provide a more globally coherent description of the inter-relations among the entire group of specific agents (see Figure 2 below). Deciding which text source(s) provide a better understanding depends on the specific research question being addressed. If we are interested in core actors, then the metrics in Table 7 indicate that the interview narrative is more coherent than the narrative provided by all sources. If we are more interested in overall coverage of the described associations among agents, then Figures 1 and 2 indicate we should use all sources.

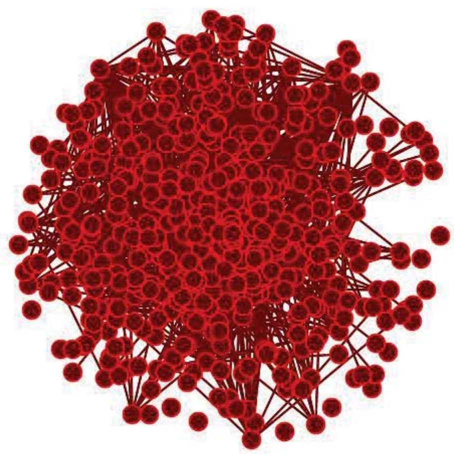

Figure 2: Agent-by-agent network formed by the union of all the texts for AM group.

In Table 8, we see that the specific agent x specific agent network formed using the text from the IRA interviews is twice as dense as the network formed by the texts from the IRA court data. From Table 8, we also see that the closeness centrality of the interview texts network is three times as that of the courts texts network. This is because the closeness centrality is a measure of the length of the links in the network, it means that on an average the lengths of the links in the interview text network is much smaller than the court texts and specific agents are more closely associated in the narrative. In contrast, the mean degree centrality of the network obtained from the courts texts is seven times as that the mean degree centrality of the network obtained from the interview texts. This implies that on an average, in the network from court texts, each agent is connected to a larger number of agents as compared to the network from the interview texts, this also shows that the court texts have agents that are highly active and each node is well known by a lot of other agents of the network.

Network measure	Interviews	Court Cases	Union
Density	0.01	0.006	0.006
Clustering coefficient	0.0	0.399	0.399
Number of Agents	25	630	643
Number of isolates	21	70	81
Link count	3.0	1266	1269
Reciprocity	1.0	1.0	1.0
Characteristic path length	1.5	2.034	2.044
Network fragmentation	0.980	0.216	0.242
Krackhardt connectedness	0.020	0.784	0.758
Krackhardt efficiency	1.0	0.995	0.995
Krackhardt hierarchy	0.0	0.0	0.0
Krackhardt upperboundedness	1.0	1.0	1.0
Degree centralization	0.125	0.861	0.844
Betweenness centralization	0.011	0.746	0.72
Closeness centralization	0.01	0.003	0.003
Eigenvector centralization	0.119	0.836	0.836

Table 8: Network level measures for IRA

The clustering coefficient of the network formed from the IRA interviews is zero, which implies that the local coherence of the aggregate interview narrative with respect to the relations among specific people is negligible. The large proportion of agents appearing as isolates (84%) provides further evidence that the IRA interview narrative provides a sparsely connected network of agents and does not illuminate relations among specific agents. This can be seen in Figure 3 below, which also implies that the clustering coefficient appears to equal zero only because we failed to specify enough significant digits in the ORA report.

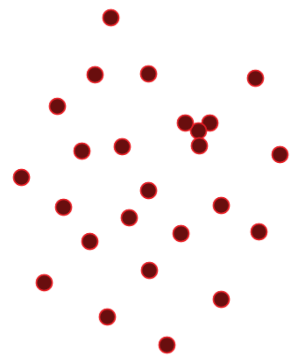

Figure 3: Agent-by-agent network formed by the texts from the IRA interviews.

On the other hand, we see that the network created from the court texts has a much higher clustering coefficient (~0.4) than the interview network – indicating that the local coherence of the IRA court narrative is higher than that of the interview narrative. This conclusion is also supported by the fact that the number of isolates is just 10% of the total number of agents in the courts texts as compared to the network formed using interviews which has 84% nodes as isolates.

Again, the visualizations indicate the need for caution when interpretting network metrics associated with the global (and local) coherence of narratives in the context of disconnected networks that have isolates, or more generally, multiple components. Thus, while the IRA interview narrative appears to be more globally coherent (given density, closeness centrality, and degree centrality) than the court- or overall narrative (see Figure 4 below), higher coherence is indicated only for a core component of four IRA agents who were associated during the the interviews. As can be seen in Figure 4 below, using all IRA sources provides better coverage of the relations among IRA agents.

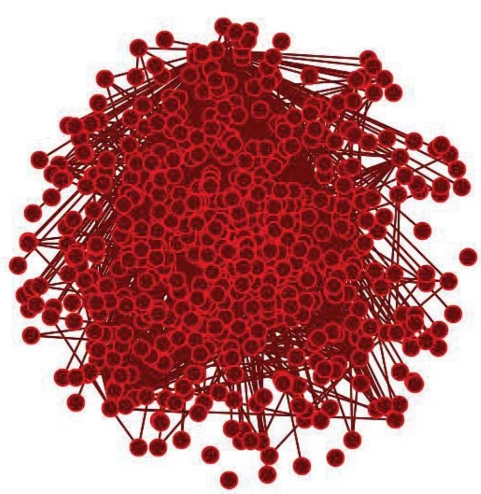

Figure 4: Agent-by-agent network formed by the union of all the texts for IRA group.

3.4 Key Organizations

In this section, the organizations associated with each terrorist group are ranked on the basis of five node-level measures (total degree centrality, hub centrality, eigenvector centrality, authority centrality, Betweenness centrality). For this analysis, we focus on interviews (i.e., primary sources), and ignore all node classes except agents and organizations. ORA's Key Entities Report identifies the 10 most important organizations. Similar to the pervious section, we perform this analysis differently for the interviews source and the union of all the sources of texts.

Figure 5: Top 10 organizations for AM according to the source -AM Interview

Figure 5 shows the top 10 organization for the network formed from the texts obtained from the interviews source. We see that the **un_world_health_organization_unwho** is most important organization in the AM interview narrative.

Figure 6: Top 10 organizations for the Al-Muhajiroun Group (Union of all the sources).

From Figure 6 above, we observe that **un_world_health_organization_unwho** organization is the second most important organization, given the narrative from all sources (union).

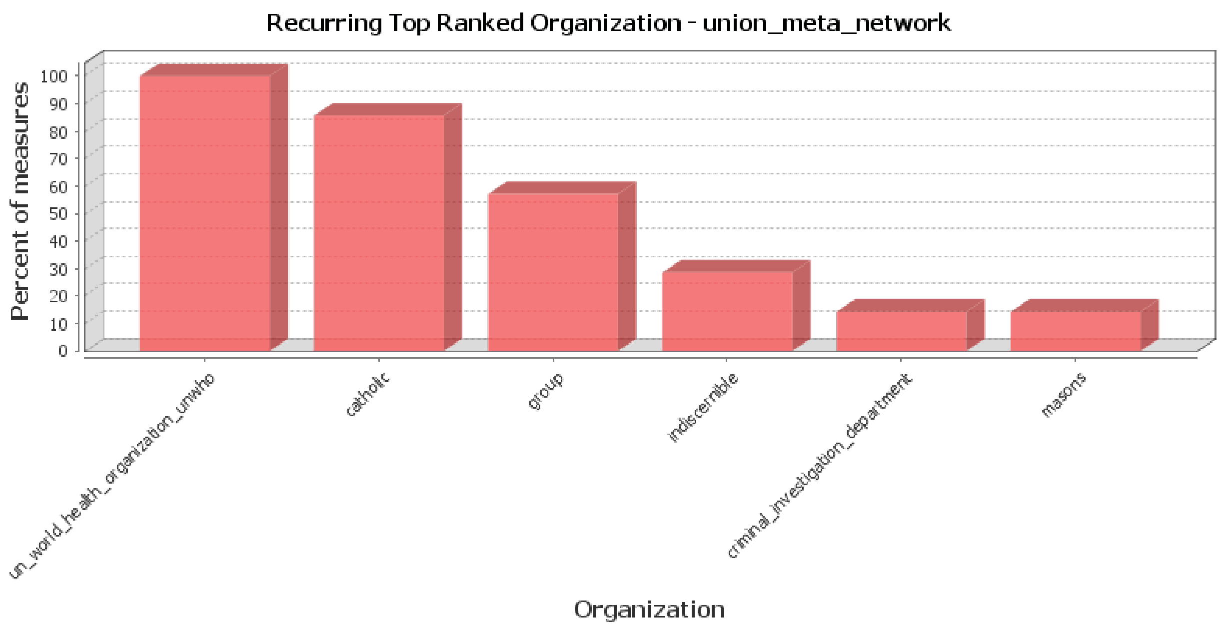

Figure 7: Top 10 organizations for IRA obtained from the interviews texts.

From Figure 7, we see that the IRA interview **narrative** also indicates that the **un_world_health_organization_unwho** organization is most important, similar to the AM interview narrative. Also, the organization ranked second in the above figure is **catholic**; this is not surprising since Ireland is originally a catholic country.

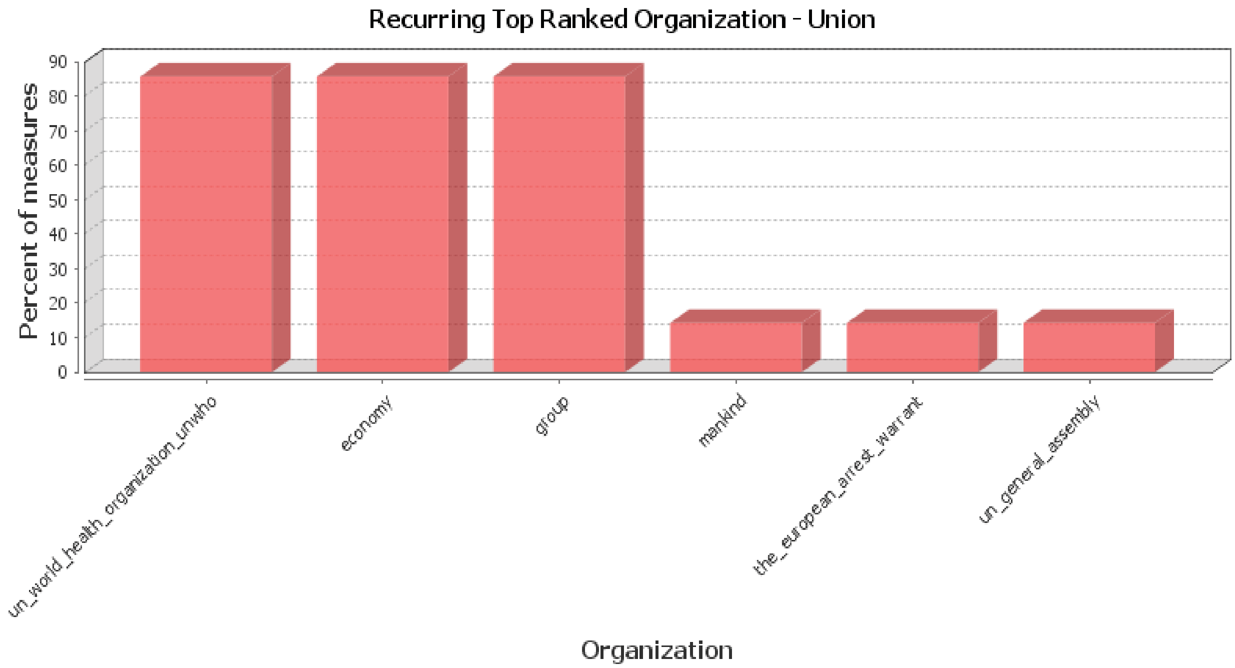

Figure 8: Top 10 organizations for the IRA Group obtained from the Union of all the sources.

Examination of the key organizations given the IRA narrative formed from all sources also indicates that the **un_world_health_organization_unwho** organization is most important (see Figure 8). Thus, the **un_world_health_organization_unwho** organization is a common link to both these terrorist groups.

4 Adaptation and Changes

In the following analyses, we recode the meta-networks described above in a manner that merges concept nodes semantically related to adaptation into one of three general adaptation keywords. To review, we group adaptation terms into three keywords for adaptation. The three key words are **Adaptation**, **Education** and **Learning**. The terms which are grouped into the key word Adaptation are terms like *adjust, alter, amend and accustom*. The terms such as *heard, idea, figured out* are grouped into the key word Learning. And similarly, the terms like *study, teach, educate* are merged into the key word Education.

In order to analyze the agents and the organizations that are involved, we ignore all other node classes like the Resources, Task, Time, and Location etc. We then, compute a 1-step sphere of influence for the three keywords of adaptation (**Learning**, **Education** and **Adaptation**), in order to see which agents and organizations have been directly associated with adaptation in the narratives from the various sources.

4.1 Specific Agents and Organizations

From Table 9, we see that the network from the AM News texts has the most number of agents attached to the adaptation keywords as compared to any other source for the Al-Muhajiroun. The network from the news texts contributes to 61% of the total agents that are linked to the adaptation keywords.

Key word	Choudry	Courts	Interviews	News Articles	Press Release	Union
Adaptation	0	4	0	2	1	6
Education	0	1	0	11	2	16
Learning	0	0	0	0	0	0
Adaptation Union	0	5	0	11	3	18

Table 9: Number of Agents in AM group directly associated with each of the adaptation keywords for each source.

The structure of the direct associations between agents and adaptation keywords in the AM News narrative is shown in Figure 9.

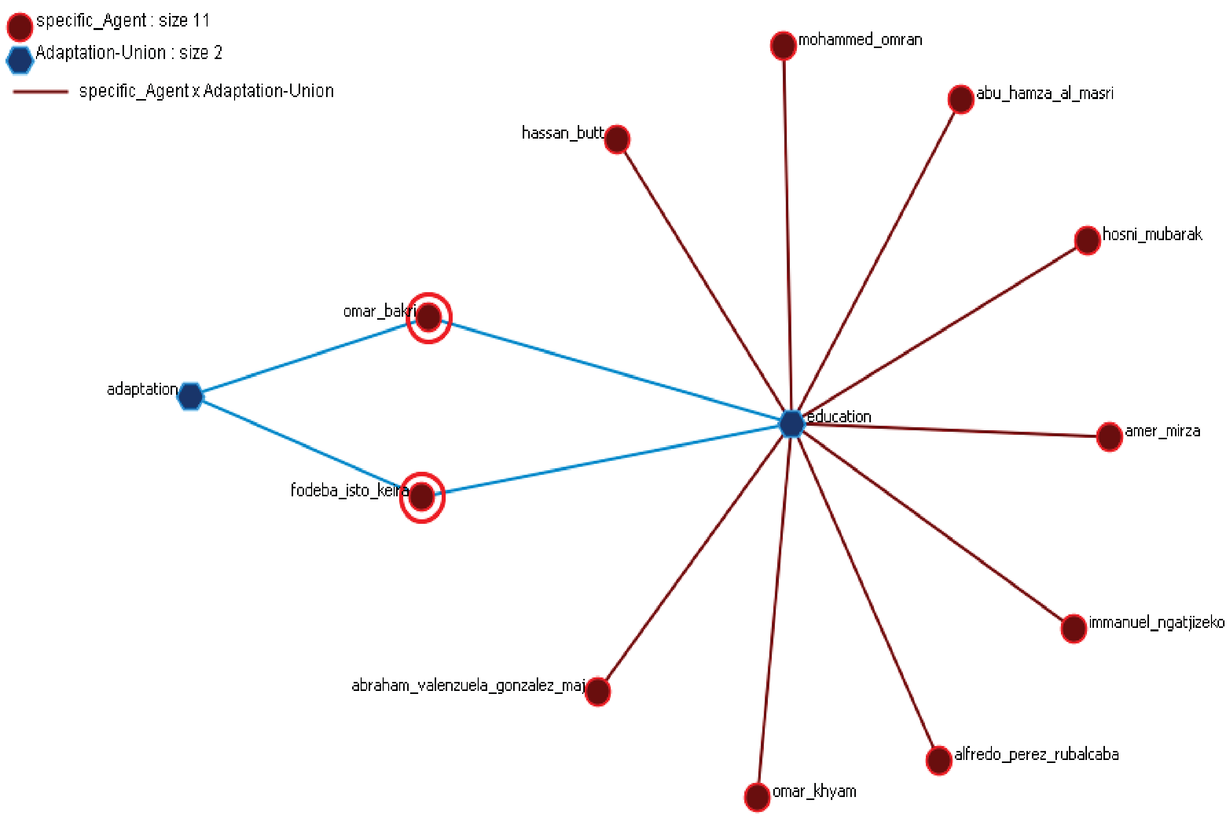

Figure 9: Specific agents directly associated with adaptation in the AM News narrative.

From Table 9, we also see that the texts from the AM choudry and the AM interview do not have any agents linked to adaptation keywords. This means that all the agents in the AM interview texts (146 specific agents in total) and AM choudry texts (34 specific agents in total) describe no agents associated with adaptation, learning and education.

None of the agents in any of the sources for the Al-Muhajiroun group is linked to the keyword **Learning** (see Figure 10).

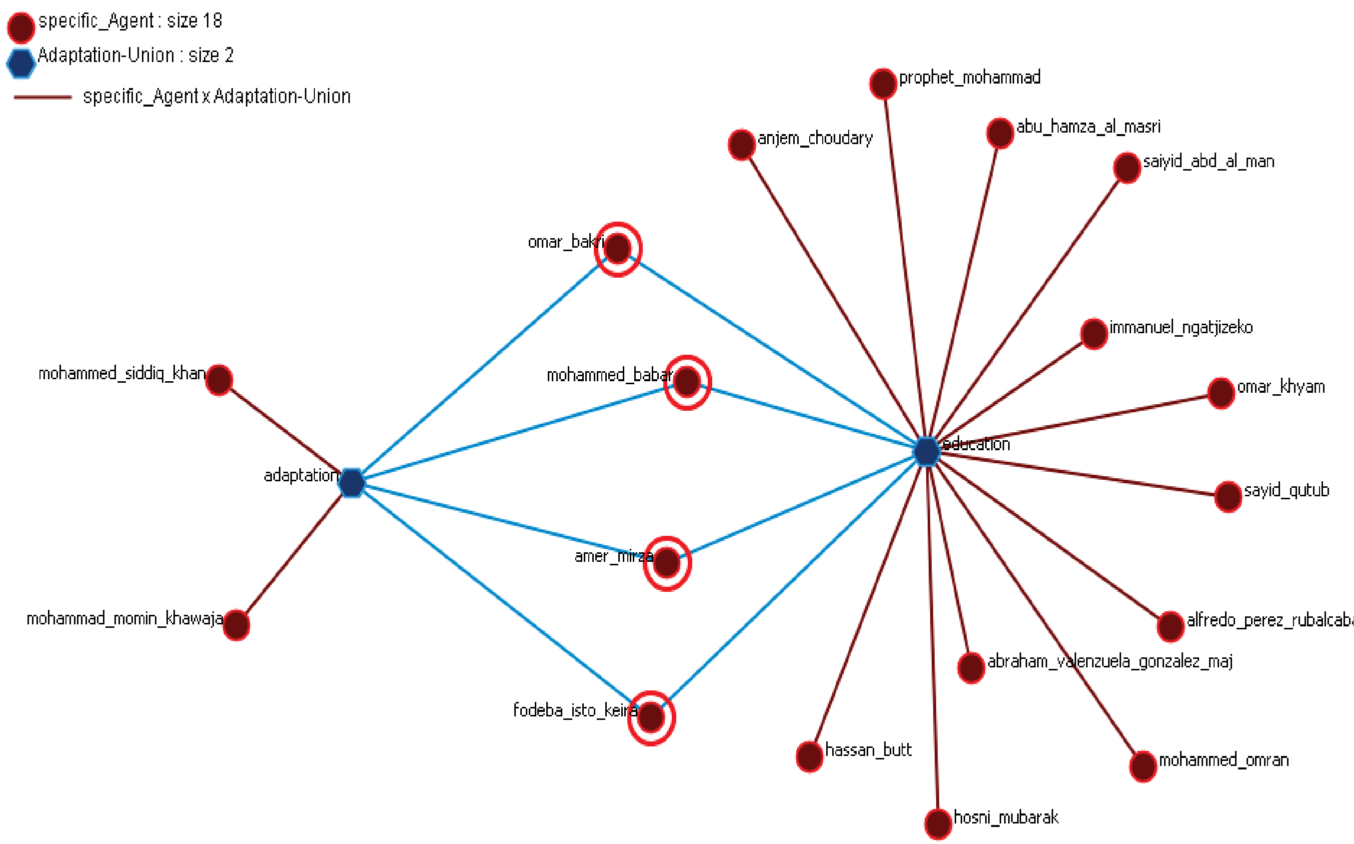

Figure 10: Specific agents directly associated with adaptation in all AM text sources (union).

From Table 10, we observe that 50% of the organizations associated with an adaptation keyword come from the source AM news.

Key word	Choudry	Court	Interviews	News Articles	Press Release	Union
Adaptation	0	2	3	10	4	15
Education	2	0	4	18	3	30
Learning	0	0	0	0	0	0
Adaptation Union	2	2	4	23	6	37

Table 10: Number of Organizations in AM group attached to each of the adaptation words for Different sources.

Figure 11shows the structure of organizations directly associated with adaptation in the AM news narrative.

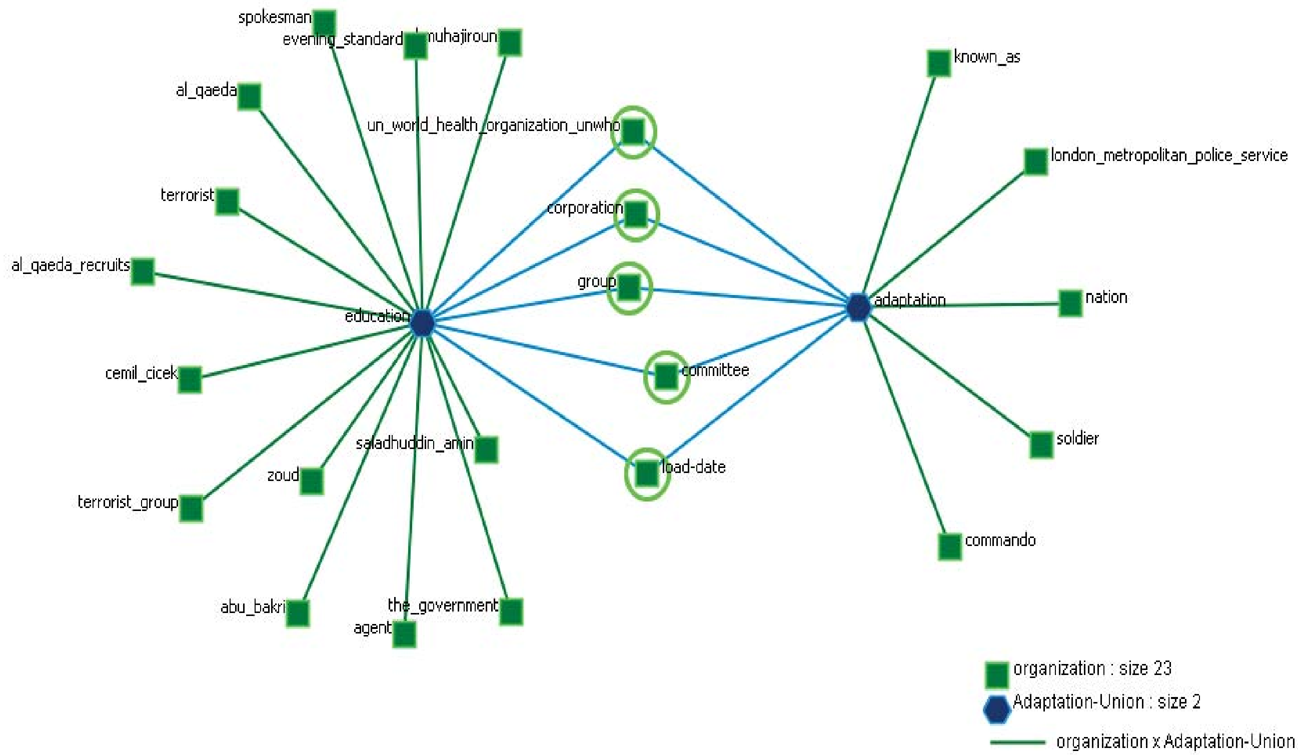

Figure 11: Organizations directly associated with adaptation in the AM News Narrative.

Also, unlike in the case of specific agents linked with adaptation keywords, Table 10 indicates we have some organization linked to the adaptation keywords from the AM interviews source and the AM choudry source as well, which collectively form 16% of the total organizations linked to the adaptation keywords. Their associative structures are shown in Figures 12 and 13, below.

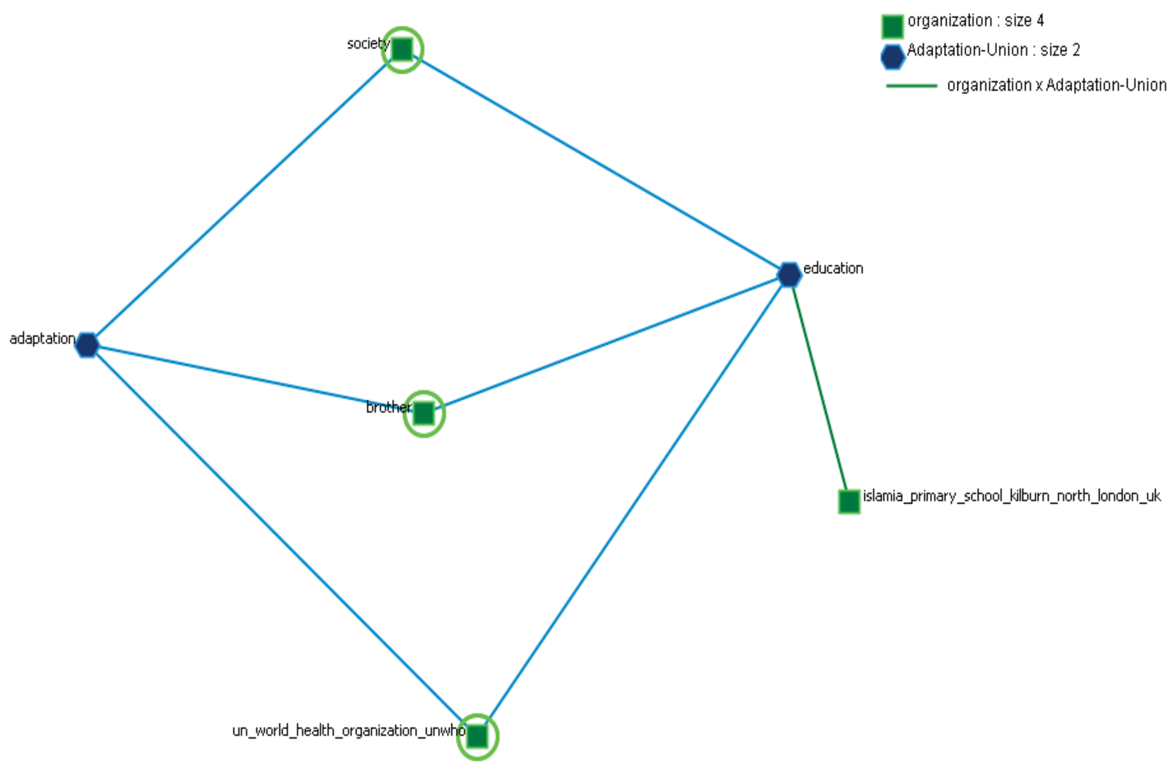

Figure 12: Organizations directly associated with adaptation in the AM interviews Narrative.

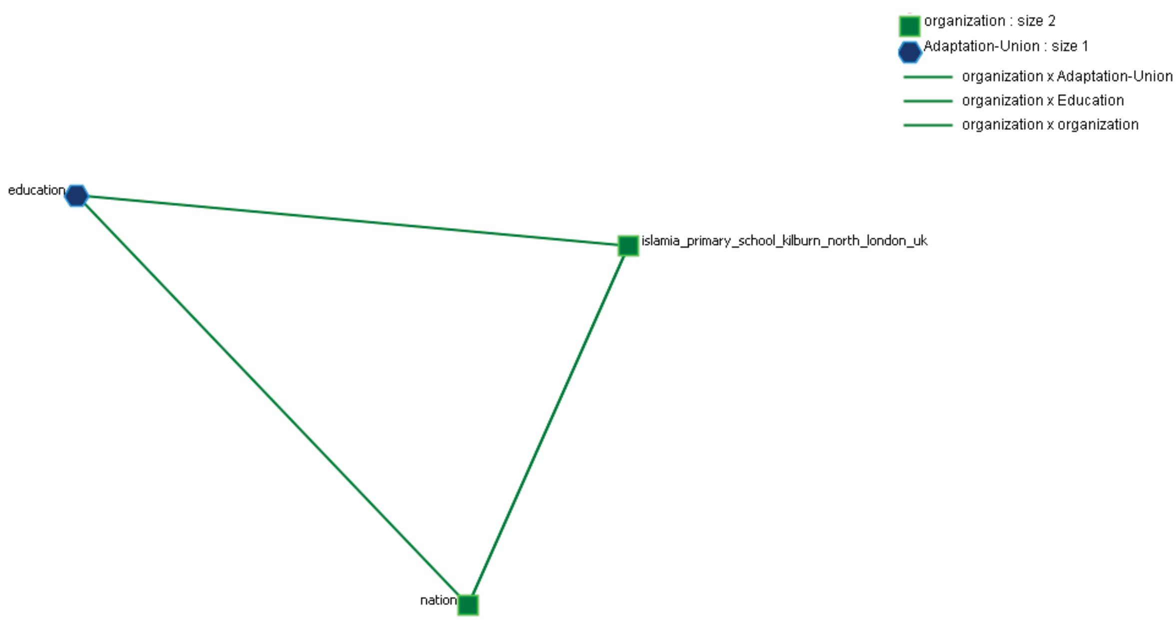

Figure 13: Organizations directly associated with adaptation in the AM choudry Narrative.

None of the organizations in any of the AM sources is linked to the key word **learning** in adaptation; this is the same observation for the agents for the AM group as well. These two observations lead us to the conclusion that there is no organization or specific agent in the AM narrative that is directly associated with **Learning** (see Figure 14).

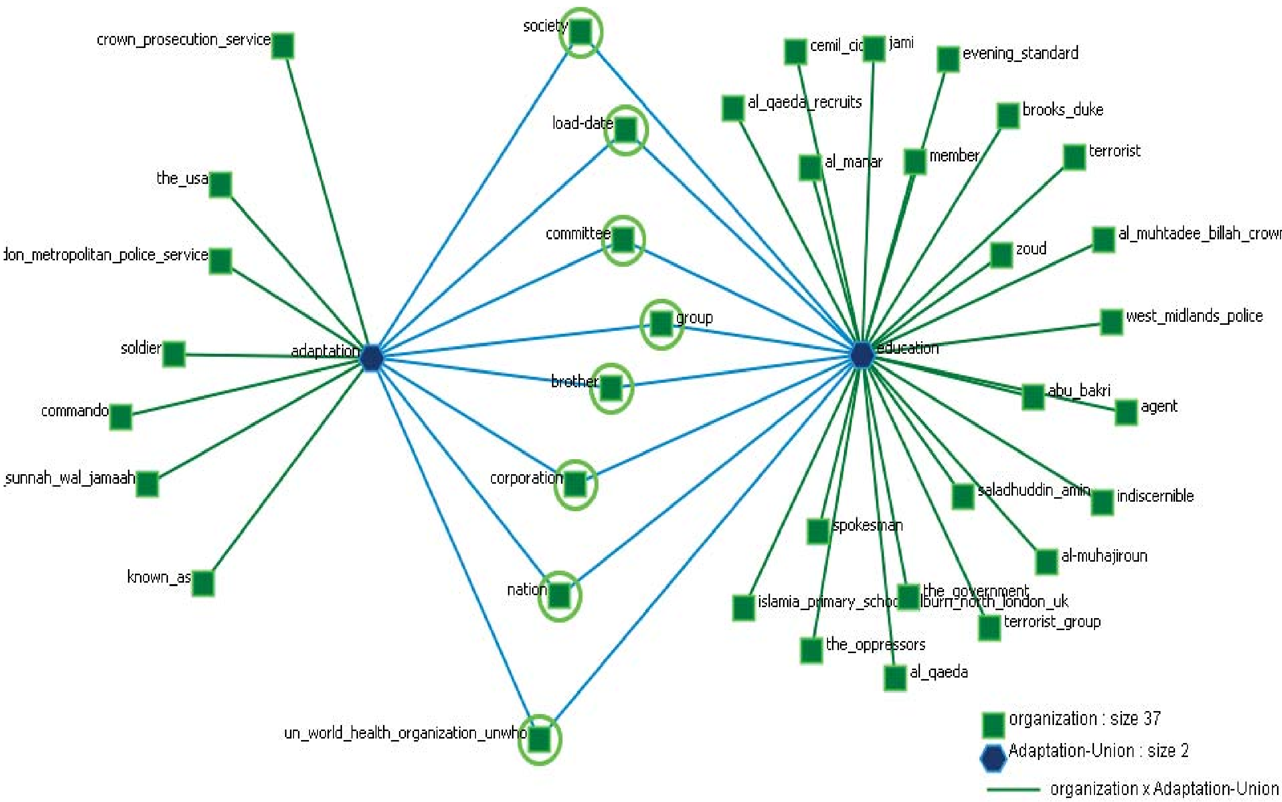

Figure 14: Organizations directly associated with adaptation in the overall AM Narrative (union).

Key word	Court Trials	Interviews	Union
Adaptation	39	0	39
Education	9	0	9
Learning	40	0	40
Adaptation Union	64	0	64

Table 11: Number of Agents of IRA group attached to each of the adaptation keywords for Different sources

Table 11 above shows the number of specific agents directly associated with adaptation in the IRA narratives. We see that no specific agents are connected to any of the adaptation keywords in the network formed using the texts from the IRA interviews. It is only the IRA court narrative that directly associates agents with adaptation. See Figure 15 for the associative structure.

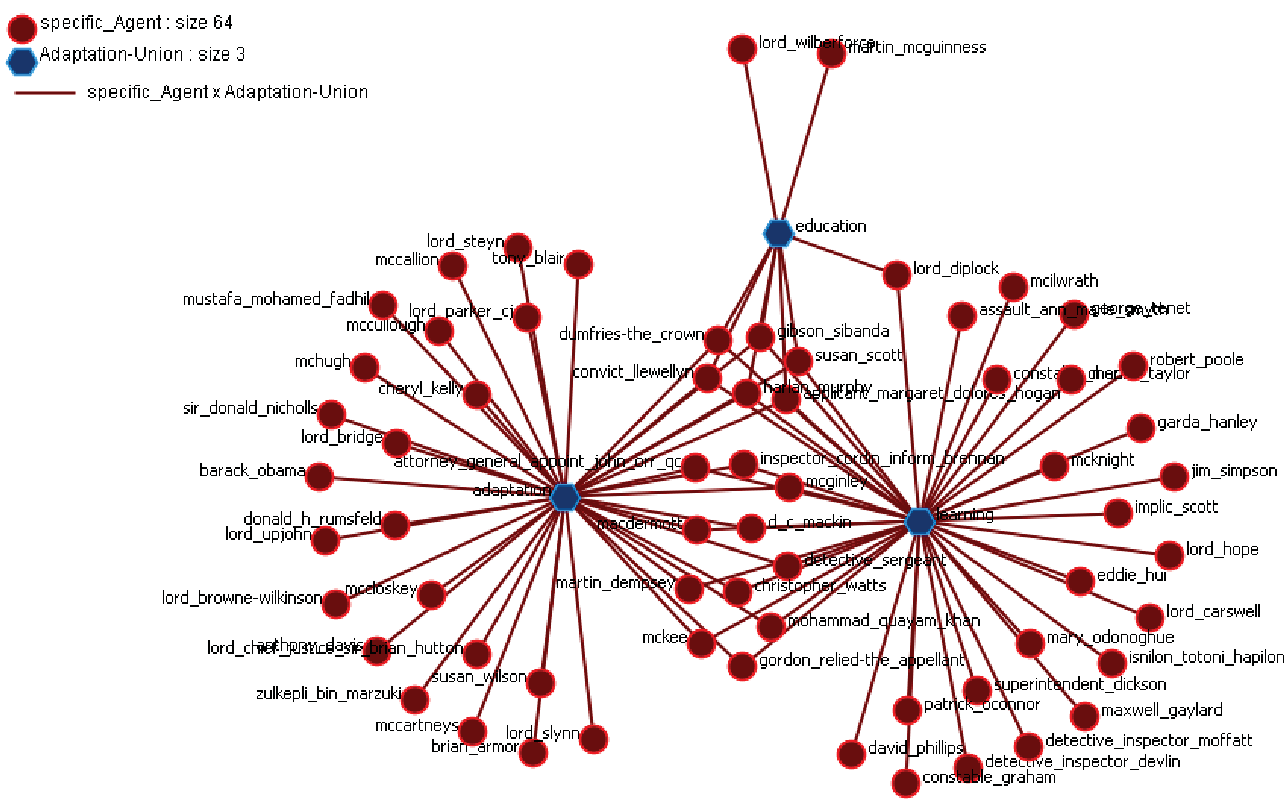

Figure 15: Specific agents directly associated with adaptation in the IRA courts narrative.

From Table 12, we observe that most of the organizations which are linked to adaptation keywords come from the Court texts (About 95% of the organizations). This means that while considering adaptation for the IRA group, the court texts dominate over the interview texts considering the agents and the organizations related to adaptation.

Key word	Court Cases	Interviews	Union
Adaptation	139	5	143
Education	45	5	48
Learning	102	8	105
Adaptation Union	223	13	228

Table 12: Number of Organizations in IRA group attached to each of the adaptation keywords for different sources.

The associative structure between organizations and adaptation keywords for the IRA court- and the union of IRA sources is shown below in Figures 16 and 17. As can be seen, information from the court narrative dominates all sources.

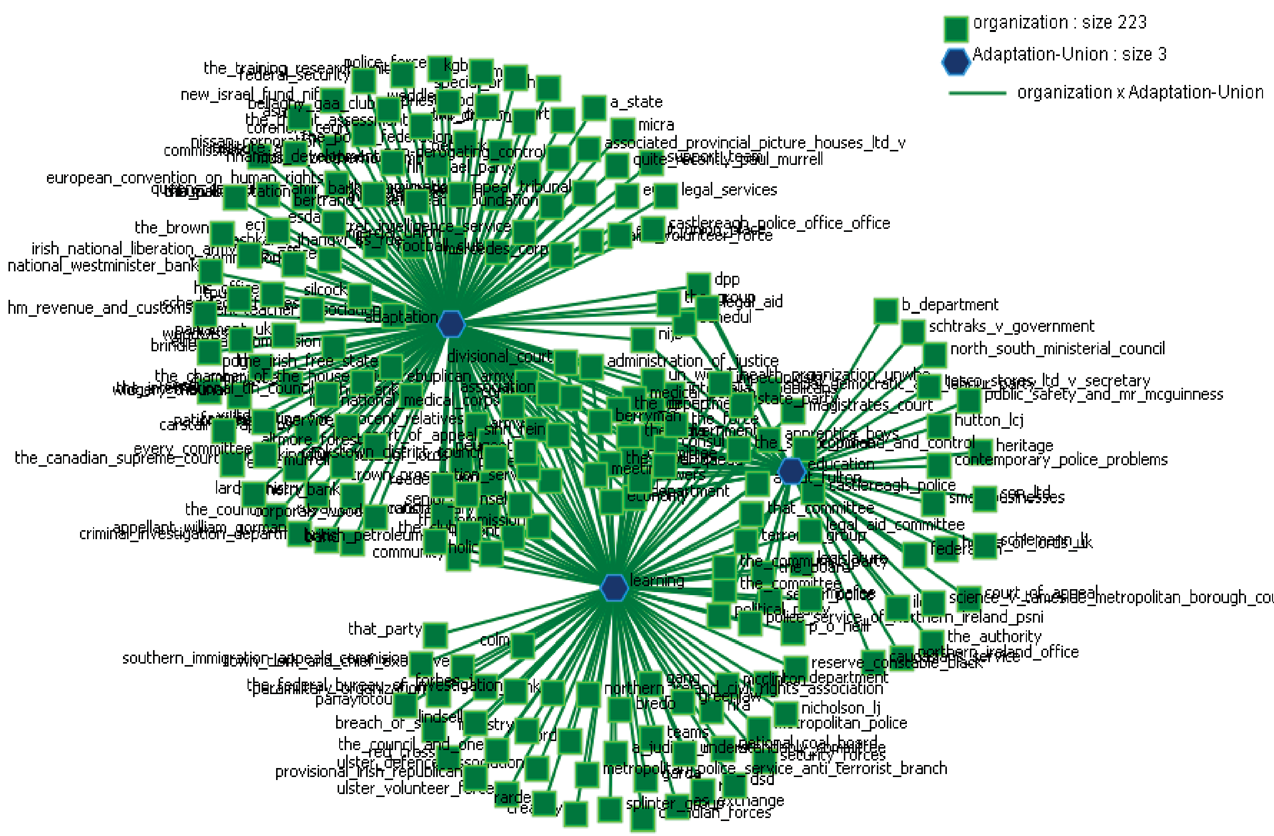

Figure 16: Organizations directly associated with adaptation in the IRA courts narrative.

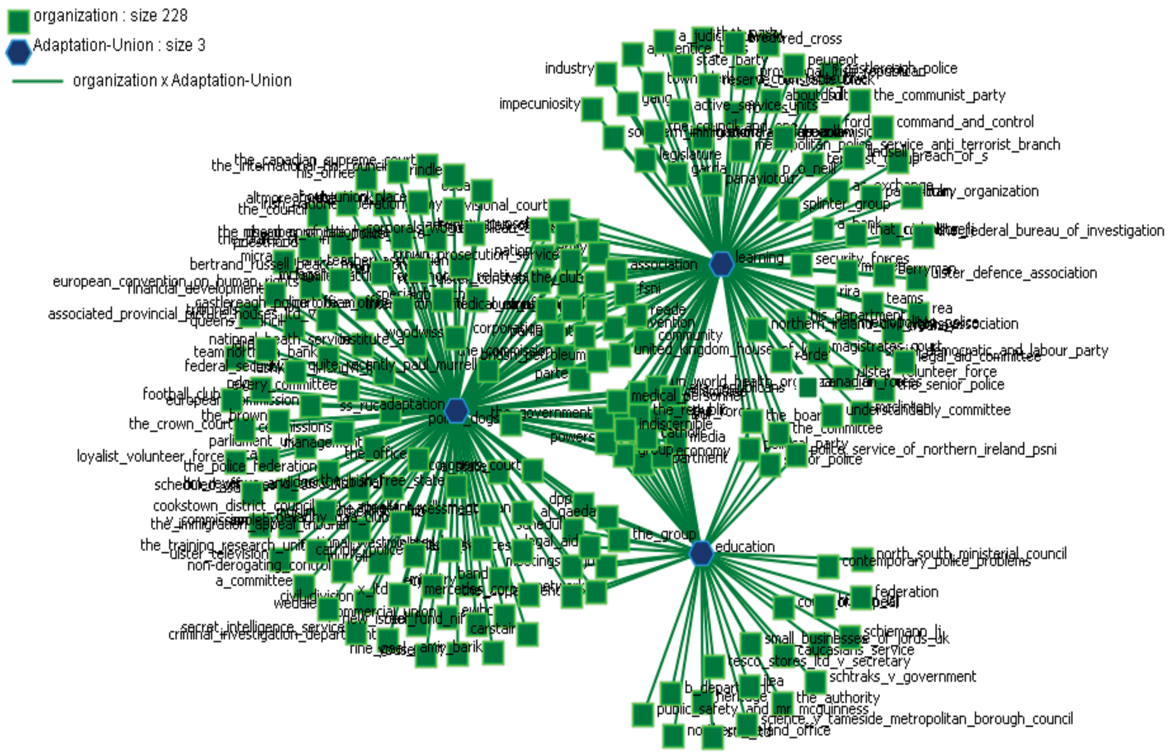

Figure 17: Organizations directly associated with adaptation given all IRA narratives.

Comparing Tables 9-12 above, we see that the AM narratives do not have any organization or agents directly associated with **learning**, whereas this is not the case for the IRA narratives. For the IRA, we observe that 40 specific agents and 105 organizations are directly associated l**earning**. Overall, the IRA narrative appears to indicate a higher degree of adaptation than does the AM narrative. When adaptation is covered in the AM narrative, it tends to be associated with general organizations and not specific people.

4.2 Self-description versus Public-perception of Adaptation

In the following analyses we divided the text sources based on whether the narratives were provided by members of the terrorist groups (self-description) or people outside the terrorist groups (public perception). For expository convenience, we will use the terms, self-description and Red (the military code for enemies), interchangeably. Similarly, we will use the terms, public perception and Blue (the military code for own force), interchangeably – even though the military color codes are not the most accurate terms in this context. Re-categorization of text sources involved dividing the interviews and court texts for both groups into Red and Blue sources, where Red sources are essentially self-descriptions and Blue sources essentially public perceptions. Texts provided by journalists (e.g., news, press) were categorized as Blue sources. After categorizing the texts as Red or Blue, we constructed new meta-networks of specific agents, organizations, and adaptation keywords. The visualizations below show 1-step spheres of influence for various sources and meta-networks.

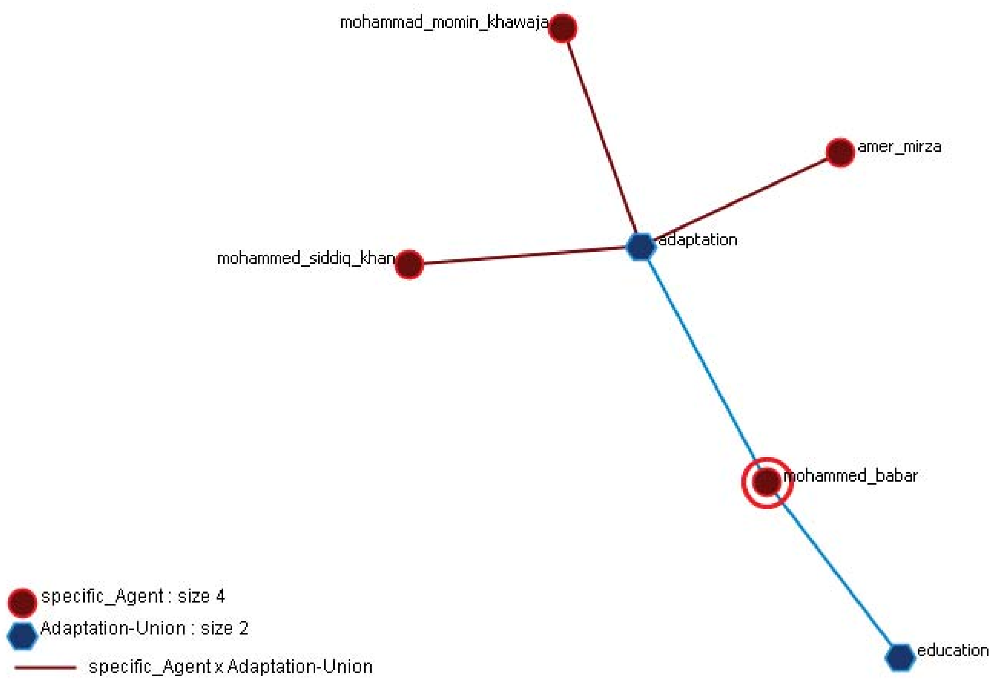

Figure 18: Self-described associations between AM agents and adaptation.

Figure 18 shows the sphere of influence involving only agents as nodes for the AM network obtained from the self-described sources like interviews with the people from the group itself. We see that the agent **mohammad_babar** is a common agent between the adaptation keywords “education” and “adaptation”.

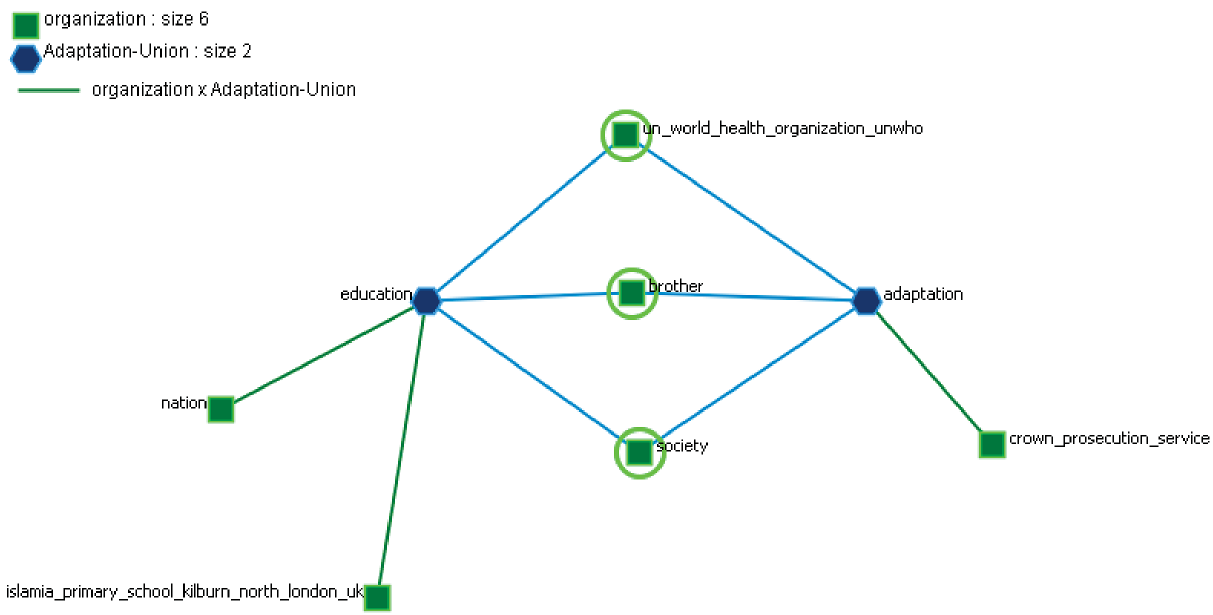

Figure 19: Self-described associations between organizations and adaptation for AM.

From Figure 19, we see that there are three common organizations between the two adaptation keywords “education” and “adaptation”. Out of the three common organizations, two are generic and one of them is specific. Organization **un_world_health_organization_unwho** is a common specific organization while considering adaptation for AM.

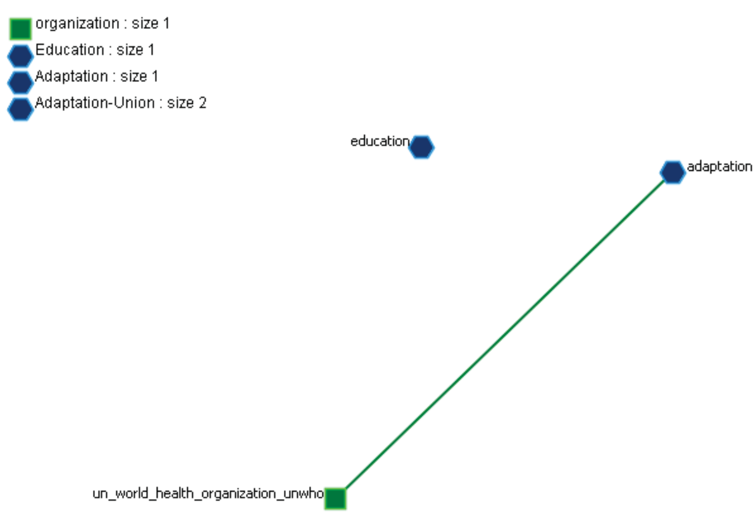

Figure 20: Public perception of organizations associated with adaptation in AM narratives

Figure 20 shows the sphere of influence for the AM group obtained using the texts from sources that are the opinion of other people like journalists or the public. Specifically, Figure 20 shows the 1-step sphere of influence for the intersection of Blue texts from interviews, courts and news for the AM. We see that result can barely be considered a network. We also observe that there is only one organization in the network that is connected to only the keyword "adaptation". The organization u**n_world_health_organization_unwho** is common between the narratives from the Blue and Red AM sources.

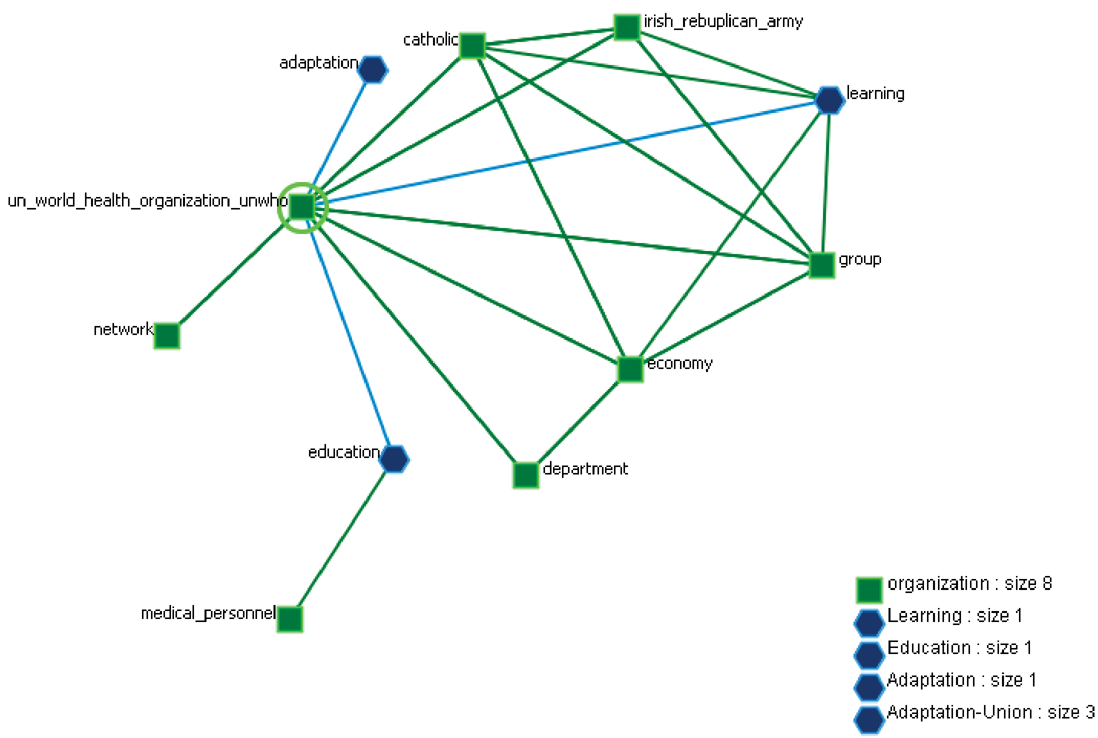

Figure 21: Self-described organizations associated with adaptation in IRA narratives

Figure 21 above depicts the 1-step sphere of influence for the intersection of Red interview and court sources for the IRA. We see that there are eight organizations that are connected to at least one of the adaptation keywords. This network appears to be more coherent as compared to the one obtained from the same sources for the AM. We see that un_world_health_organization_unwho is a common organization for each of the three adaptation keywords. This is a common scenario in both the groups (AM and IRA) and common between different the narratives for the same groups also.

5 Conclusion

The IRA narratives were more conceptually diverse than the AM narratives. Most IRA concepts were extracted from the IRA court source; whereas most AM concepts were extracted from the AM news source. Narratives associated with both groups tended to use generalities when referring to people (agents). The global coherence of narratives about both groups appeared similar when the types of entities discussed was ignored. When we distinguished among the types of entities in the narratives (e.g., specific agents, organizations, tasks, etc.), we found that the global coherence of IRA narratives tended to be lower than that of the AM narratives.

Our examination of how the narratives described associations among specific people (agents) indicated that if we are interested in maximal coverage of the relations among agents we should use all text sources. Based on all sources, we can conclude that the global coherence of narratives concerning specific-agent associations is about the same for both groups; but IRA narratives are more locally coherent than AM narratives. Considering specific sources available in the CATNET data, AM interviews stood out among AM sources because it provided coherent information about a small core set of actors in the midst of many isolated actors. In contrast, IRA court texts stood out from the IRA sources because it provided coherent information about relations among the majority of actors described, with few isolated actors. If interest places more importance on self-description (i.e., narratives from group members) than on coverage, then either of these sources (AM interviews, IRA court) appears to be a good candidate for further analysis.

Examination of the data for key organizations indicated that the World Health Organization is important to the narratives associated with both groups.

Overall, the narratives indicate that competitive adaptation was more important for the IRA than for the AM. Moreover, adaptation was of similar importance in self-described sources and public perception. These findings may be related to the influence that radical Islamic doctrine has on the global coherence of AM narratives as compared to IRA narratives. On the other hand, it is possible that the increased global coherence of AM narratives is an artifact of the AM news as a dominant source of data in the AM narrative. Accordingly, western journalists may provide a limited perspective on the AM, which would increase the global coherence of the narrative. Thus, the importance adaptation in AM narratives may appear lower than that in the IRA narratives because doctrine eschews change or because of a bias in our data, or a little of both.

The AM narrative has 18 specific agents and 37 organizations that are directly associated with adaptation. This is in contrast to the IRA narrative, which directly associates 64 specific agents and 228 organizations with adaptation. In Table 13, we have compiled a list of the key agents and organizations deemed central in the study of adaptation and changes for the Al-Muhajiroun group (AM). The listed four agents and seven organizations are the concepts that are common to the adaptation keywords **Education** and **Adaptation**.

Central Key Agents	Central Key Organization
Omar_bakri	Society
Mohammad_babar	Load-date
Amer_mirza	Committee
Fodeba_isto_keira	Group
	Brother
	Corporation
	Un_world_health_organization_unwho

Table 13: Key central agents and Organization for AM

Table 14 shows a list of six key agents and 16 organizations deemed central to the study of adaptation and changes in the Irish Republican Army. These are concepts that are common to all the three adaptation keywords (**Adaptation**, **Learning** and **Education)** for the IRA narrative.

Central Key Agents	Central Key Organizations
convict_llewellyn	The_goverment
dumfries-the_crown	Group
gibson_sibanda	The_force
harlan_murphy	Media
susan_scott	Economy
applicant_margaret_dolores_hogan	Consul
	Powers
	The_republic
	Catholic
	Medical_personnel
	Committee
	Department
	Media
	Inter_alia_republicans
	Indiscernible
	Un_world_health_organization_unwho

Table 14: Key central agents and Organization for IRA

6 References

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