A Network Analytics Report

How to diffuse positive opinions of AI on the trading floor

1. **Introduction**

This study aims to explore the network of 192 traders from Canary Wharf and their opinions towards AI. The relationship in this network is an undirected network of knowledge exchange in terms of technical and industry proficiency between traders. In addition to the interaction between traders, their physical location will also be evaluated to identify the distribution of AI attitudes on the trading floor. The analysis will be utilised to suggest recommendations for the diffusion of positive AI opinions among traders.

2. **Analysis**

2.1 Knowledge exchange network

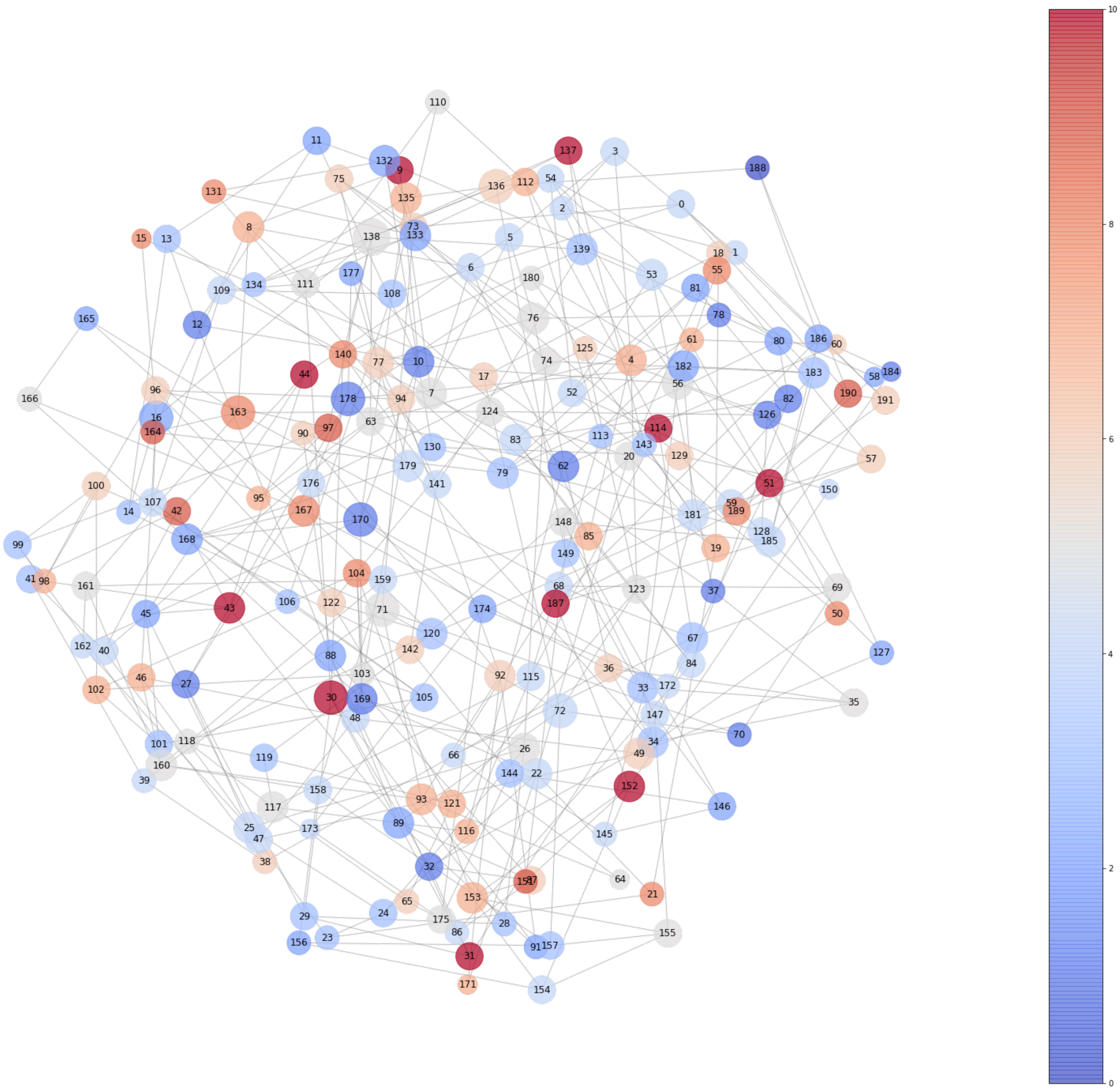

Figure 1. Knowledge Exchange network

Figure 1 demonstrates the knowledge exchange network between traders in which the node label indicates the trader's ID.The node size is based on their degree within the network in which traders with more connections have a bigger node size. The node color indicates their attitudes towards AI - blue represents negative attitude, grey represents neutral, and red represents positive.

Overall, all the traders on the trading floor are connected in which the network is one connected component. The network has relatively more negative attitudes (blue color nodes) than positive attitudes (red color nodes). However, it shows more intensive red nodes than intensive blue nodes which suggests there are more traders with significantly positive AI attitude. The majority of bigger size nodes are in blue color which indicates traders with relatively more connections tend to have a negative AI attitude. Moreover, the graph also shows that traders do not have the same AI attributes with the traders they share knowledge with. This is supported by our dyadic similarity analysis results where traders on the trading floor have an average difference of 2.38 in AI opinion with their connected nodes (Figure 2).

	Dyadic similarity
count	384.000000
mean	2.382812
std	2.013484
min	0.000000
25%	1.000000
50%	2.000000
75%	3.000000
max	9.000000

Figure 2. Dyadic similarity

2. Traders' physical layout

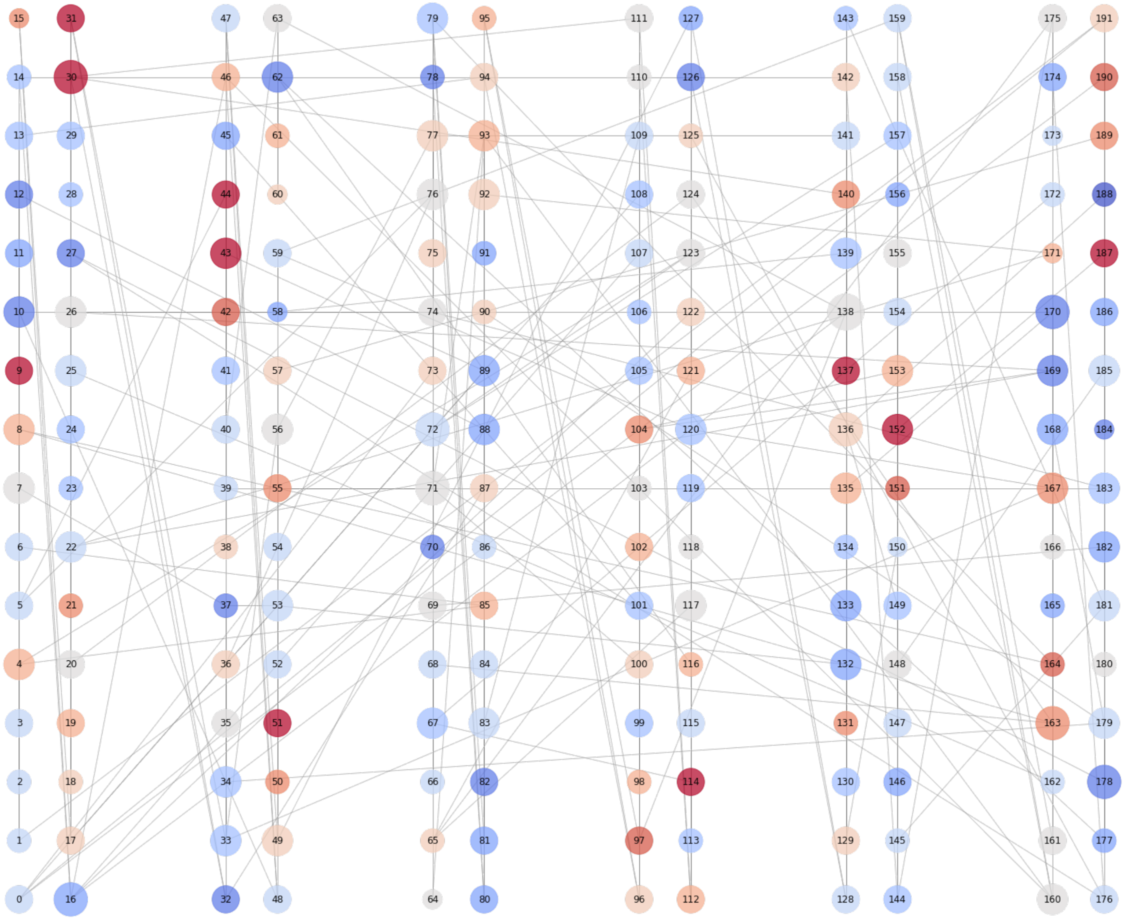

Figure 3. Physical layout of the trading floor

Figure 3 maps the seating position of the traders along with their connections within the network. This graph indicates the majority of traders share knowledge with their neighbouring traders. Moreover, it is evident that traders that are sitting together do not necessarily share similar AI attributes, which reflects the same result as figure 2.

3. Degree distribution

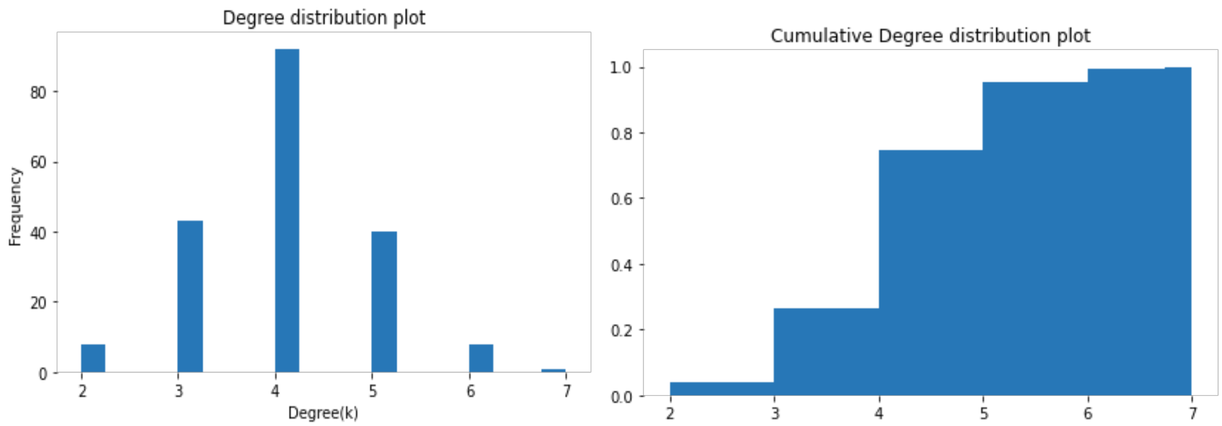

Figure.4. a) Degree distribution b) cumulative degree distribution

Most of the traders have an average of 4 connections in the network and the maximum connection for a trader is 7 (Figure 4). From the betweenness centrality graph (Figure 5), it is observed that the overall betweenness centrality is low, with a maximum of 0.3. This demonstrates the bridging role played by the nodes with the highest betweenness centrality is limited and they are not effective in facilitating information flow in the network (Golbeck, 2015). Information is not easily passed between communities in which this can decelerate the diffusion of AI opinions.

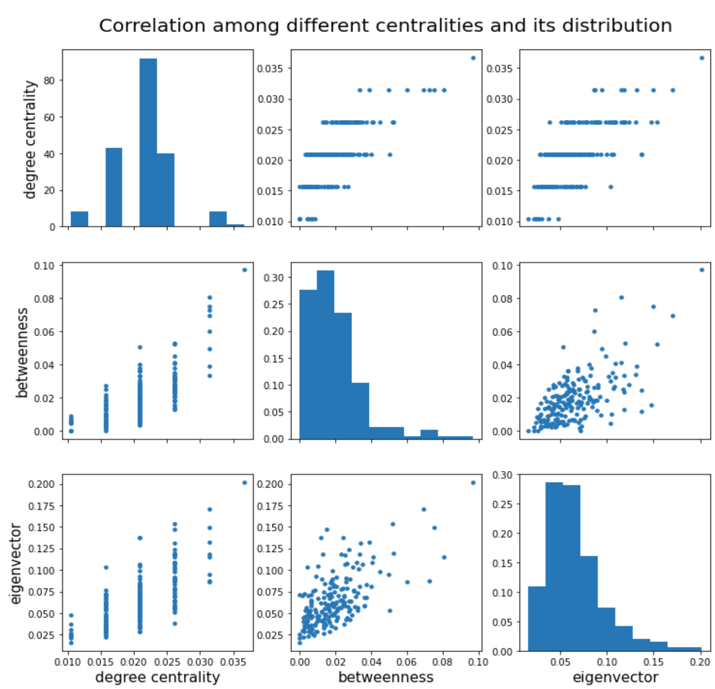

Figure.5. Correlation plot of three Centralities

4. Cascading Behaviour

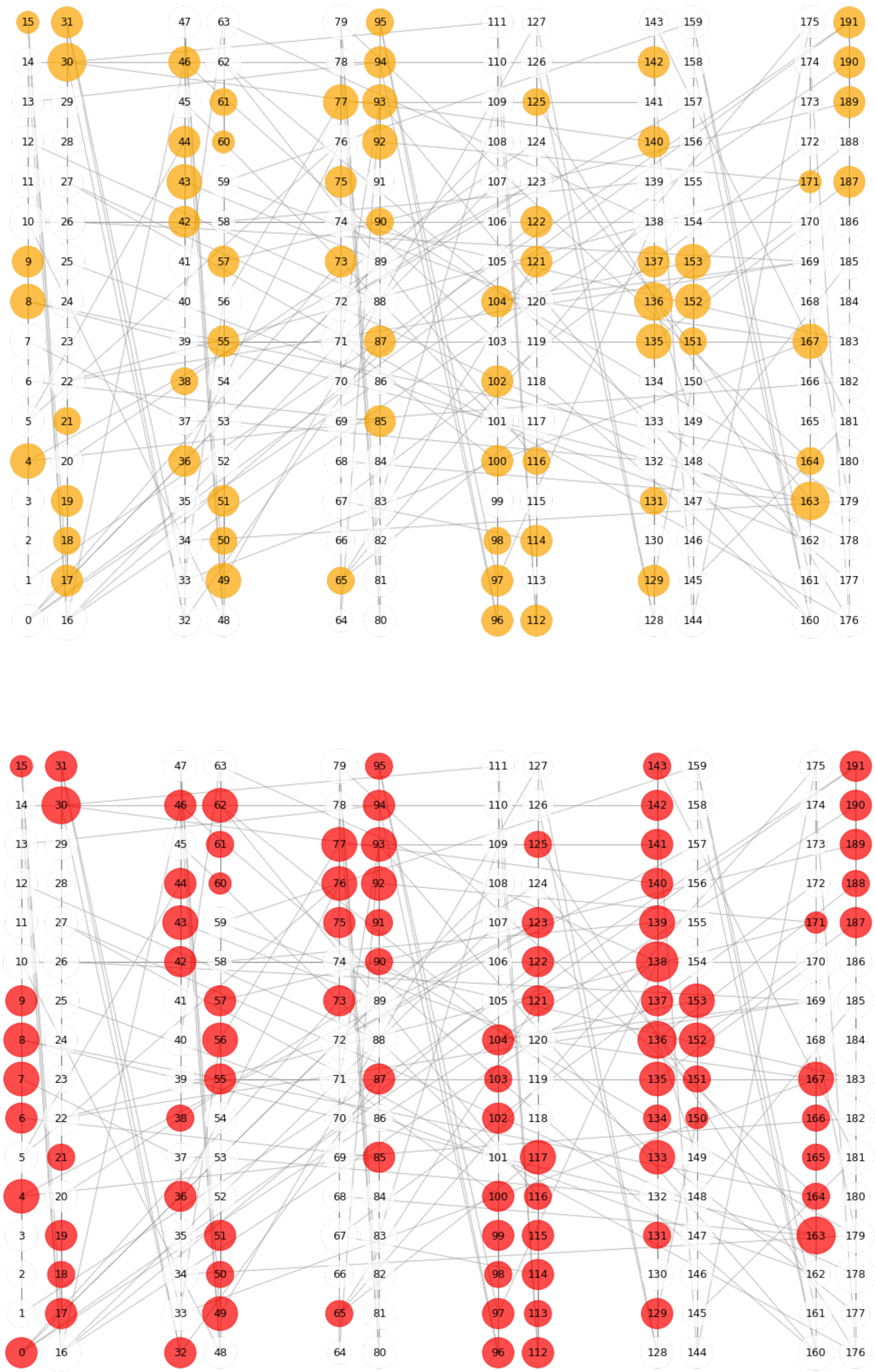

Figure 6. a) The early adopters b) The adopters

Figure 6 initalises the diffusion process of positive AI opinions on the trading floor influenced by early adopters in the network. The early adopters are chosen as the traders who have AI attitudes higher than 5 (64 nodes) as they have already established a positive attitude. As shown, the diffusion process spread to more than half of the network, with an additional 60 traders being influenced.

For the nodes that did not adopt, their average degree is 4.023 and average betweenness centrality is 0.02 (Figure 7). Particularly, this group has a maximum betweenness centrality of 0.097 which is a relatively low value. This suggests that the traders in this group have strong ties within their community and are less connected to others that are in a different community. Thus, they have less access to the novel information that is circulating around the network and be influenced by the choice of the nodes from a different community (Easley and Kleinberg, 2010). Such weak connection reduces their extent to gain information that are not available through their other social ties; Hence, it is identified as one of the obstacles for the diffusion.

	degree	betweenness
count	128.000000	128.000000
mean	4.023438	0.019825
std	0.917587	0.016167
min	2.000000	0.000000
25%	3.000000	0.008505
50%	4.000000	0.016948
75%	5.000000	0.026700
max	7.000000	0.096939

Figure 7. Descriptive statistics for nodes that did not adopt

Moreover, it is evident that the cascading behaviour only diffuses from early adopters to their neighboring nodes, but not the nodes opposite them (graph 6). This suggests the layout of the desk can also be an obstacle for diffusion. The computer separation of the desk can reduce the communication of the traders that are sitting opposite to each other which limits knowledge exchange.

5. Recommendations

In order to promote the diffusion of positive opinions about AI, different strategies have to be adopted to target different groups of traders. For traders that already have a positive AI opinion, it is suggested to invite an outside expert and set up an AI-related pilot project for them in order to integrate their AI knowledge and to reinforce their interest. They are then able to influence other traders through a more informative approach. For potential adopters and non-adopters, public talks by AI consultant can be hosted to introduce them the capabilities of the technology in a business context. This proposition allows them to get familiar with AI incrementally and yield their potential of adoption. Furthermore, a digital chat group including all the traders can be established to accelerate interactions and enable extensive information flow for the traders that have less connections.

Reference

Easley, D., & Kleinberg, J. (2010). Cascading behavior in networks. *Networks, Crowds, and Markets: Reasoning About a Highly Connected World. Cambridge University Press*.

Golbeck, J., (2015). Introduction to Social Media Investigation. *Syngress*.