Q1. How do traders' opinions map onto the knowledge exchange network?

In order to understand a link between AI preferences and knowledge exchange, the nodes' colours were set to AI preferences and positions to the seating arrangements fig1).

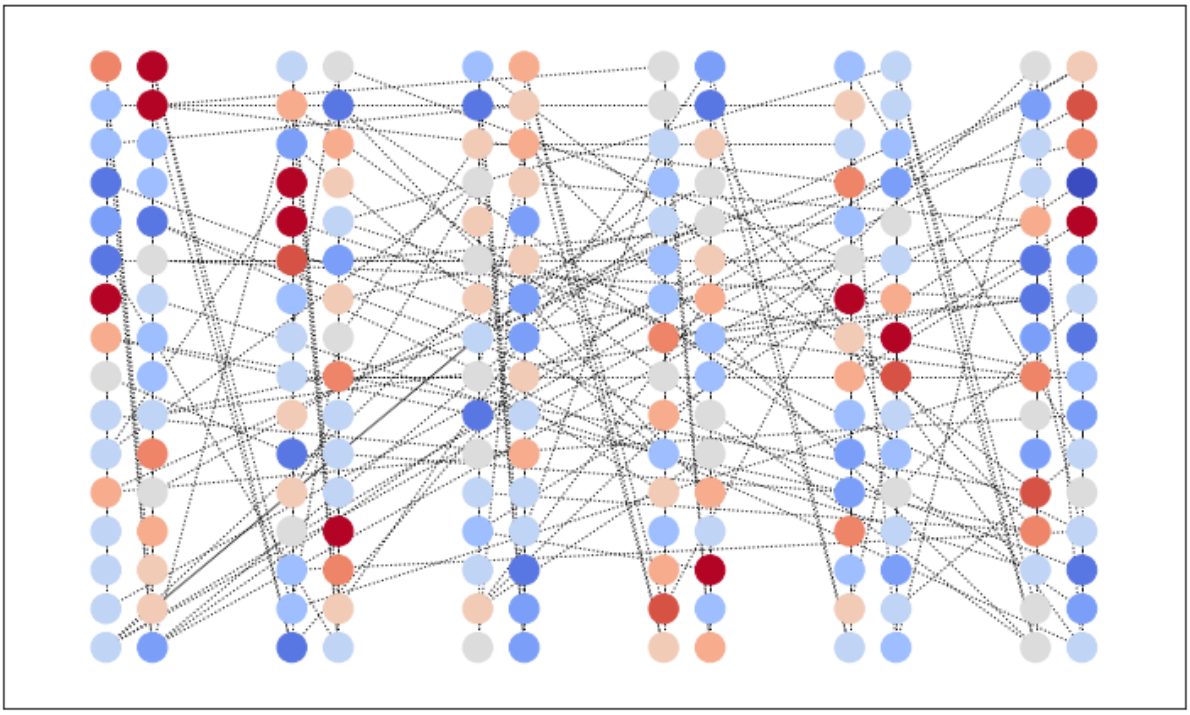

fig 1

Although some similar AI preferences were connected, there was no apparent confirmation. To further investigate the AI opinions across affiliations, the nodes were resized reflecting AI opinions and colours communities (fig2)

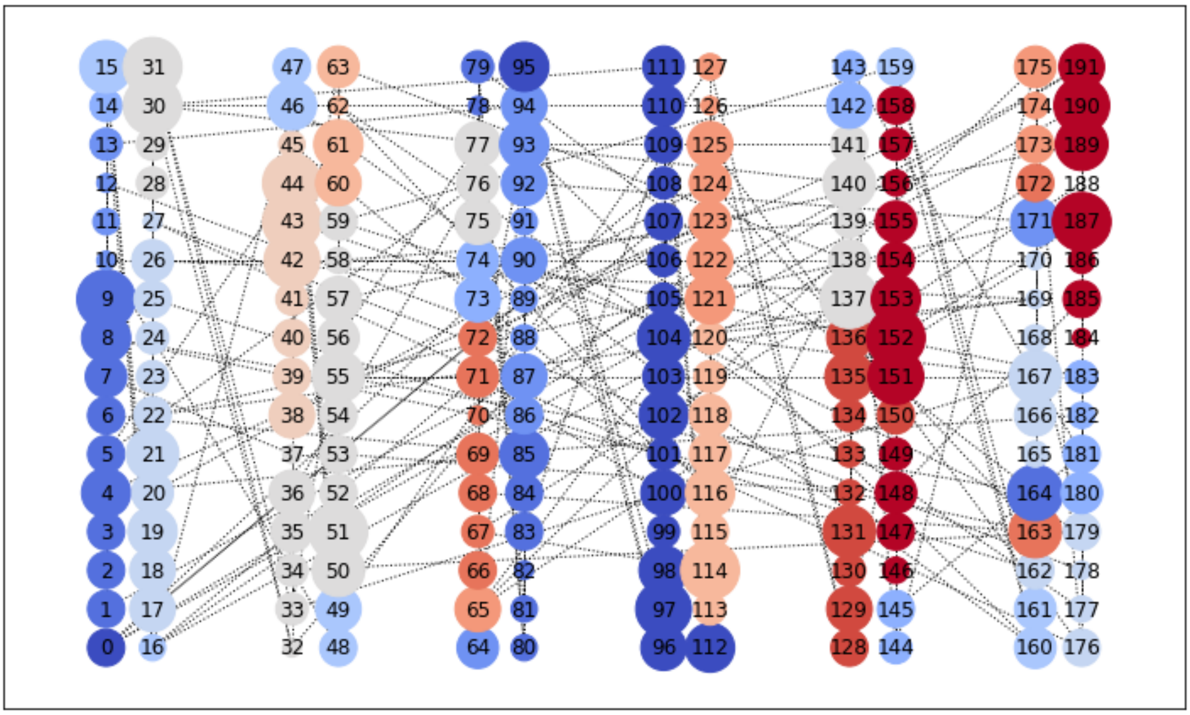

fig 2

More nodes with low AI preferences linked and those with higher AI preferences were spread across different communities. The ratios of high AI preferences to low AI preferences nodes were calculated for each community because the means may be influenced by community sizes. The binary classification of nodes helped capture pro AI (preference>5) communities, 33% pro AI traders overall the network. No community showed a concentration of pro-AI nodes, but 2 communities comprised of less than 20% pro-AI nodes whereas the maximum was 50% for all communities; most others stayed within the 33% region as the network (Appendix1). Traders forming communities based on shared domain knowledge is prominent in traders with low AI opinions. The common scepticisms towards AI could be forming these communities; anti-AI nodes may connect with pro AI nodes (since 1 in 3 nodes is pro AI) but then seek affiliation to other common nodes.

The nodes with high betweenness centrality are not pro-AI. Node 138 has the highest centrality based on 4 centrality measures (Appendix2) but neutral AI preference, whereas its neighbours' AI preferences are quite diverse. In fact, most central nodes are neutral towards AI, which might be propagating the centrality.

Q2. How do traders' opinions map onto the physical layout of the trading floor?

The proximity in trader's placements may entail similarity in AI opinions; this was examined through the same visualisation mimicking the traders' seating (fig1).

Diverse levels of AI opinions were scattered around the floor and in some instances similarly shaded nodes appeared either adjacently or oppositely seated. The community formation showed a strong dependency on the proximity of the nodes - most nodes of most communities were positioned close together in the same or adjacent rows (fig2).To verify whether the AI opinions were influenced by traders' placements, node-to-node distances and the magnitude of their AI opinion differences were calculated. The distances were plotted and OLS was used to examine the significance of proximity in predicting AI preferences between nodes. The distance between nodes is the simple distance between their x and y coordinates. The lineplot (fig3) did not reveal a discernible pattern.

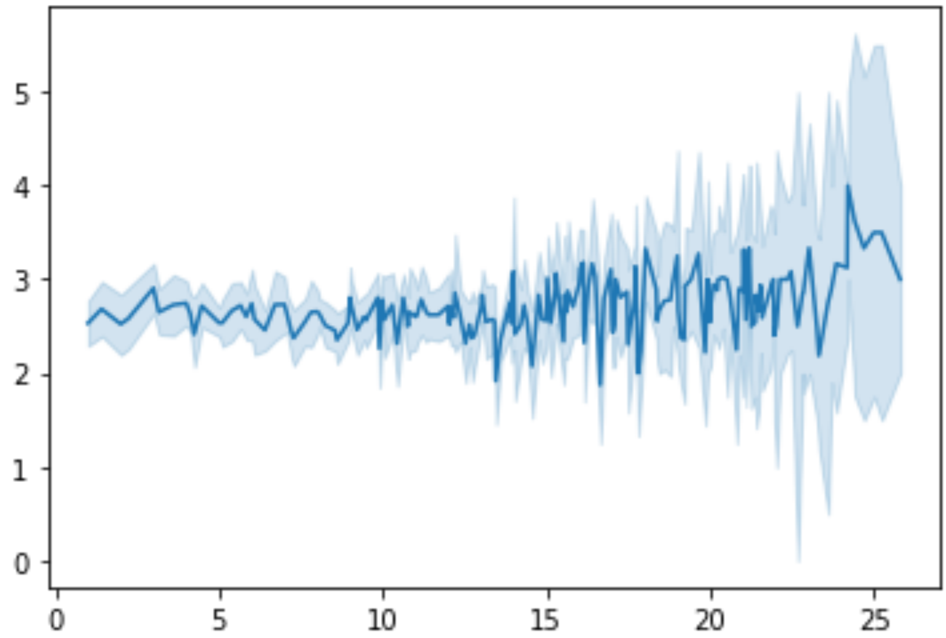

fig 3

The OLS resulted in a significant but a miniscule coefficient for distance, so the impact, if any, might be negligible (Appendix3). The R-squared was almost zero so the fit is questionable. Hence, the proximity between the traders does not affect the AI opinions between them.

Q3. What is the network-related obstacles to the diffusion of positive opinions about AI in the trading floor?

To classify the early adopters of positive AI sentiments, their opinions above a chosen threshold were used. Node-level payoffs were assigned by weighing average AI preferences of adopting (a) and not adopting neighbours (b) with that node's own AI preference – taking into account the node's inclination/disinclination towards AI and how neighbours scaled it.

Node 138 (highest eigenvector centrality) played a key role in the diffusion. With AI preference of 5, if this node is an early adopter, it causes an almost twice the percentage increase in AI adopters after diffusion as compared to when it is not an early adopter (Appendix5).

Similarly, at threshold 7, node 9 became an early adopter activating its community member (Appendix 6); implying that when some nodes in community get influenced, the other nodes become more likely to absorb that influence.

The opposite can be true and impede the flow of positive AI opinions. Node 72 (community 10 with 11.1% pro AI nodes, average AI opinion of 4.2) – did not diffuse for many iterations and neither did the other nodes in community 10 until the threshold was dropped to 4.

163 was a pro-AI node and the diffusion only occurred when 71 and 69 became the early adopters and cascaded the influence across the community. This creates the opportunity to investigate the internal influences within clusters and how their collective notions can resist diffusion and less central sub-node's (163) individual influence.

After studying the diffusion process using multiple thresholds, node 188 did not diffuse at all, even at threshold 0. With a degree of 3 and low centralities, node 188 may not be well integrated in the knowledge exchange network to receive enough payoff.

Q4. What is your recommendation to promote the diffusion of positive opinions about AI in the trading floor?

As examined in the diffusion, the impediments were strongly negative communities (Easley and Kleinberg, 2019) and weakly integrated nodes. Powers of well-connected and central nodes are instrumental if correctly optimised to promote the diffusion of opinions. Pro-AI traders are omnipresent across communities, however, their influence on their communities needs assistance from other nodes. There are only two tough communities (10 and 3) and to penetrate them, individual nodes with high eigenvector and betweenness centralities (Parau et al., 2017) and neutral to high AI opinions (node 138 and 135) must be leveraged by making them adopt at the earliest. The goal is to continuously increase the number of adopters in any given node's neighbourhood and thus maximise its payoff (mirroring viral marketing). The highly social traders can be rewarded for promoting AI and disseminating its advantages across their connections (Wang and Street, 2018). These traders can be regarded as influencers who then increase the payoffs of the surrounding nodes so much that they form a hierarchy of messengers across the network; eventually even the less integrated trader's (188) payoff increases through indirect influence. Essentially with the resisting communities, it is more about attaining a higher volume of early adopters which might be achieved by the viral behaviour of highly social traders.

References

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Parau, P., Lemnaru, C., Dinsoreanu, M. and Potolea, R. (2017) "Opinion Leader Detection", *Sentiment Analysis in Social Networks*, pp. 157-170. doi: 10.1016/b978-0-12-804412-4.00010-3.

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